

Modeling Lane-changing Behavior in Presence of Exclusive Lanes

by

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Abstract

Driving behavior is significantly affected by the presence of exclusive lanes. Particularly, unlimited access to exclusive lanes result significant amount of special type of lane-changing actions. The objective of this thesis is to develop an improved lane-changing model that has a generalized structure and is flexible enough to capture the lane-changing behavior in all situations including the presence of unlimited access exclusive lanes. A new lane-changing model with explicit choice of target lane is proposed in this regard.

The target lane is the lane the driver perceives as the best to be in taking a wide range of factors and goals into account. The direction of the immediate lane change is based on the choice of this target lane rather than myopic evaluation of adjacent lanes. A lane change occurs in the direction implied by the chosen target lane depending upon gap availability. The parameters of the model are jointly estimated with detailed vehicle trajectory data and calibrated for a situation with unlimited access High Occupancy Vehicle (HOV) lane. Estimation results show that the target lane choice is affected by lane-specific attributes, such as average speed and density, variables that relate to the path plan and the interactions of the vehicle with other vehicles surrounding it. The model is validated and compared with an existing lane-changing model using a microscopic traffic simulator in an HOV lane situation. The results indicate that the proposed model is significantly better than the previous model.

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Chapter 1

Introduction

Microscopic traffic simulators are becoming increasingly popular as evaluation and planning tools for transportation improvement initiatives. Lane-changing behavior models are important components of these microscopic traffic simulation tools. Lane-changing behavior can be influenced by numerous factors including lane-configurations and access control measures. Particularly, presence of exclusive lanes (e.g. HOV lanes, HOT lanes, ETC lanes etc.) can significantly affect lane-changing behavior. This thesis presents a lane-changing model that has a generalized flexible structure and is applicable in all situations, including presence of exclusive lanes.

This chapter first presents an overview of the congestion problem and the contribution of exclusive lanes in remedial of the congestion. The motivation for this research is then presented followed by the research objectives and the outline of the rest of the thesis.

1.1 Congestion Management

Traffic congestion is a major problem in urban areas all around the world. According to the Urban Mobility Report (TTI, 2004), traffic congestion has resulted in a loss of 3.5 billion hours of productivity in major US cities alone, incurring a loss equivalent to \$63.2 billion in the year 2002. Though vehicle ownership is much lower in the developing countries (38 vehicles per 1,000 inhabitants compared to 585 vehicles per 1,000 inhabitants in Western Europe), the congestion situation is equally bad in most cities of the developing countries and expected to get worse (Schwaab, 2002). These concerns make congestion alleviation a major transportation priority.

Traffic congestion can be viewed as an imbalance of supply and demand. Typically, traffic congestion mitigation measures have therefore been classified as either supply

based or demand based approaches. The recent trend is however to integrate both approaches and implement strategies that seek to induce demand adjustments through supply-based actions. Each category of congestion management measure is summarized below:

a) Supply Based Approaches

Supply based approaches basically refer to increasing the physical capacity by constructing more roads. However, building more roads may provide only modest congestion reduction benefits over the long run, since a significant portion of added capacity is often filled with induced peak period vehicle traffic (Rebound Effects). In the long run, additional road construction encourages additional development in the vicinity leading to further growth in traffic. An analysis performed on delay experienced by drivers in urban areas between 1982 and 2002 (TTI, 2004) indicated that changes in roadway supply have an effect on the change in delay, but it appears that if additional roads are the only solution used to address mobility concerns, the growth in facilities has to be at a rate slightly greater than travel growth in order to maintain constant travel times (Figure 1.1).

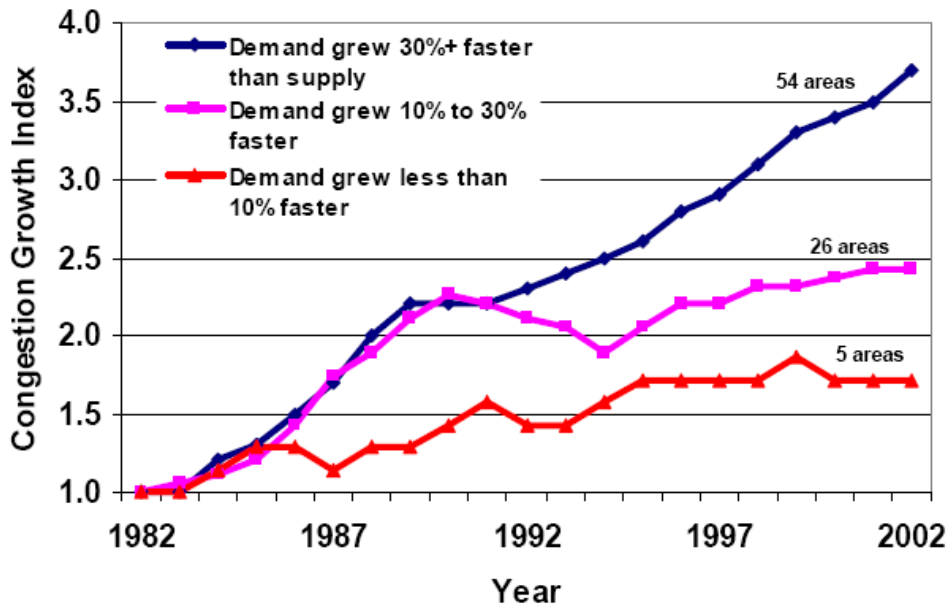


Figure 1.1 - Road growth and mobility level

(Source: Urban Mobility Report, TTI 2004)

Besides, high construction costs, land scarcity and environmental constraints limit the construction of new roads to increase the physical capacity required to meet the continuing growth in travel demand in urban areas.

b) Demand Based Approaches

Travel demand management strategies aim to alter driver behavior to reduce the temporal and spatial peaking of demand. The strategies of this type include road pricing, commute trip reduction programs, flexible work schedules (that allow employees to travel off-peak), transit-oriented regional development, community-based car-sharing etc. However, the success of these measures is highly dependent on public acceptance and participation. The demand based approaches are generally insufficient to provide significant congestion reduction if they are not implemented on a large scale and are unable to influence a major portion of total peak-period travelers.

c) Integrated Demand and Supply Based Approaches

These include Advanced Traffic Management Systems (ATMS), Advanced Traveler Information Systems (ATIS), Incident Management Systems and Managed Exclusive Lanes (HOV lanes, tolled lanes, reversible and contra-flow roadways, truck-only facilities etc.). These approaches not only make use of the transportation system to the best extent possible and increase the efficiency and reliability of the system, but also contribute to alter the driver behavior in a positive manner. In this thesis we will focus on exclusive lanes.

1.2 Exclusive Lanes

Exclusive lanes restrict the usage of certain lanes to specific types of vehicles. The vehicles are generally designated by vehicle class, occupancy level or payment type. The most common types of exclusive lanes include:

- **High Occupancy Vehicle (HOV) Lanes:** These lanes are restricted to vehicles with a minimum specified occupancy and may include carpools, vanpools and buses. When implemented on highways, HOV lanes can be separate lanes with access points at limited fixed locations, or they can permit unlimited access to

concurrent flow lanes (that is, an eligible vehicle can enter or exit the HOV lanes at any point). HOV priority provides travel time savings, operating cost savings and increased travel reliability. HOV lanes typically provide time savings from 0.5-minute per mile on arterial streets up to 1.6-minutes per mile on congested freeways (Pratt, 1999) and have a significant role in congestion reduction (qualitatively shown in Figure 1.2).

- Value-Priced and High Occupancy Toll (HOT) Lanes: Value-priced or tolled lanes offer the drivers improved level of service in return of a charge that may be fixed throughout the day or vary depending upon the level of congestion. HOT lanes are special types of HOV lanes that allow vehicles with lower occupancy to have access to the exclusive lane by paying a toll. The idea behind HOT lanes is to improve HOV lane utilization as well as to generate revenue.
- Heavy Vehicle Lanes: Heavy vehicles, generally buses and trucks, are often provided with an exclusive operational lane to reduce the conflicts with other vehicles. Bus lanes provide an incentive for riders to use transit by decreasing delay. Truck lanes are designed to increase overall speed and safety.
- Electronic Toll Collection (ETC) Lanes: When approaching a toll plaza, these lanes segregate vehicles opting to make electronic toll payments and ensure speedy transactions.

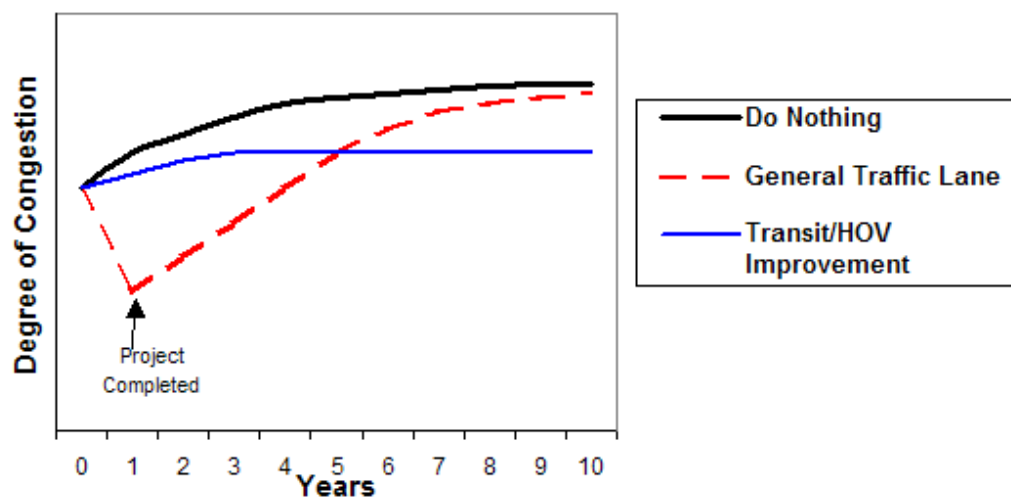


Figure 1.2 - Road Widening and Transit/HOV Improvement Congestion Impacts

(Source: Online TDM Encyclopedia, Victoria Transport Policy Institute)

1.3 Motivation

Complex traffic characteristics are observed in presence of exclusive lanes. Therefore, conventional analysis methods based on static traffic assignment techniques are generally inadequate for design and analysis in such scenarios (Mahmassani et al 2001). Field tests are also not feasible because of prohibitively high costs and lack of public acceptance. Furthermore, the usefulness of such field studies is deterred by the inability to fully control the conditions under which they are performed.

Microscopic traffic simulation tools, which analyze traffic phenomena through explicit and detailed representation of the behavior of individual drivers and mimic the real world traffic situations, are ideal tools to analyze and experiment with different exclusive lane design and control strategies in a controlled environment. Driving behavior models are an important component of such microscopic traffic simulation tools. These models include speed/acceleration models, which describe the movement of the vehicle in the longitudinal direction, lane-changing models, which describe drivers' lane selection and gap acceptance behaviors, etc.

However, since driving behavior is significantly affected by presence of exclusive lanes, normal driving behavior models are often not directly applicable in presence of exclusive lanes. Particularly, unlimited access to exclusive lanes results in significant amount of special type of lane-changing actions that are not observed in conventional roadway situations. For example, an exclusive lane, with its much higher LOS, attracts eligible vehicles from lanes further away and these vehicles tend to make multiple lane-changes to get to the exclusive lane. The state-of-the-art driving behavior models do not have the capability to accommodate these special types of lane-changing behavior and hence the associated microscopic simulation tools are not applicable in the analysis of exclusive lanes.

Thus, there is a need to develop more realistic lane-changing models that can capture the complexity of the lane-changing process in presence of unlimited access exclusive lanes.

1.4 Objectives

The objective of this thesis is to develop a framework for modeling the lane-changing behavior in presence of exclusive lanes, estimate the model with the available data and test its effectiveness by implementing it in a microscopic simulation tool. The improved lane-changing model should have a generalized and flexible structure that is capable of capturing the lane-changing behavior in all situations including in presence of exclusive lanes. The generalized model should overcome the limitations of the existing lane-changing models and fill the present gap in this arena.

1.5 Thesis Outline

The remainder of this thesis is organized in six chapters. In Chapter 2, a literature review on research related to exclusive lane choice and existing lane-changing models is presented. Chapter 3 presents the framework and structure of the proposed lane-changing model. The estimation and calibration methodology developed for the model and the available data for that purpose is described in Chapter 4. The estimation results are presented in Chapter 5 followed by the calibration and validation results of the model using a microscopic traffic simulator in Chapter 6. Finally, conclusions and directions for further research are summarized in Chapter 7.

Chapter 2

Literature Review

Modeling lane-changing behavior in presence of exclusive lanes involves the integration of two types of models: exclusive lane choice models and lane-changing models. The relevant research works on these models are discussed in this chapter along with their limitations.

Previous researches involving exclusive lane choice principally focused on assessing the demand for exclusive lane usage and its sensitivity to different external factors. But these aggregate models are not detailed enough to be implemented in the microscopic simulation tools. On the other hand, there have been considerable research on lane-changing behavior of drivers in general, but lane-changing behavior in presence of exclusive lanes has not been studied extensively. The existing lane-changing models cover situations with limited access exclusive lanes to some extent, but no literature is available on lane-changing behavior in presence of unlimited access exclusive lanes. This chapter summarizes the overall limitations of the exclusive lane-choice models and existing lane-changing models.

2.1 Exclusive Lane Choice

Many researchers have used travelers' mode choice behavior to model exclusive lane usage and the impact of exclusive lanes on the network. Discrete choice models, such as multinomial logit (MNL) models have been widely used in such mode-choice models. Most of these models are planning models developed for quantifying the effects of adding the exclusive lane or evaluating different geometric configurations. There is also a set of models that have been developed for analyzing exclusive lanes in the operational

level. These two types of models are discussed below followed by their respective limitations.

2.1.1 Planning Models

Dahlgren (2002) used a mode-choice model combined with a queuing model for analysis of HOV lane usage. The choice between making a trip via HOV and via a non-HOV (single occupant vehicles in most cases) was assumed to be a function of the attributes of the two alternatives and of the characteristics of the person making the trip.

The important attributes of the HOV alternative include travel time, travel cost, waiting time and inconvenience associated with arranging the carpool, and ambience in the waiting area. The traveler attributes include regularity and flexibility of working hours, work and home locations, childcare requirements, income and auto availability. The probability that an individual will choose an HOV lane is expressed as:

$$P_{HOV} = \frac{e^{\sum \beta_i H_i}}{e^{\sum \beta_i H_i} + e^{\sum \beta_i L_i}} = \frac{1}{1 + e^{\sum \beta_i L_i - \beta_i H_i}} \quad (2.1)$$

Where, β_i are the coefficients of attributes and H_i and L_i are the traveler and modal attributes related to the HOV and LOV trips respectively. The model has been developed to evaluate the impacts of adding an additional HOV vs. adding a mixed flow lane and only the effect of change in travel time after addition of the new facility is considered in the analysis. The mode-choice equation is therefore reduced to:

$$P_{HOV} = \frac{1}{1 + \gamma e^{\sum \beta_i (T_L - T_H)}} \quad (2.2)$$

Where, β_i is the coefficient of travel time, T_L and T_H are the travel times via mixed-flow and the HOV lanes respectively. γ accounts for the effect of all other attributes. The coefficient of travel time is assumed to be the same in both types of lanes and based on literatures on sensitivity to travel time in general, rather than on rigorous estimation. In congested situations, T_L is calculated using queuing models.

Since choice of HOV lane is dependent on level of congestion (that varies from time to time), the travel time used in Equation 2.2 was based on the proportion of people that have chosen the HOV option in the previous intervals. It was noted however that in the

real world, travelers do not have minute by minute estimates of travel time, rather they make some assessment of the potential travel time gain using the HOV lane over the course of days, traveling at similar times or under similar delay conditions, and then weigh that against the other benefits and costs of using an HOV.

Fielding et al (1994) studied the effects of electronic road pricing and used travel time and travel cost as explanatory variables for exclusive lane choice. Chu (1993) acknowledged the effect of departure time in choosing HOV modes and estimated a two-level nested logit model with mode and departure-time choice. In this model, an HOV delay penalty has been introduced in the utility of HOV to represent the time spent creating the carpool each morning.

Noland et al (2001) extended Chu’s model to a three-level nested logit model with mode choice, lane choice and time of day choice (Figure 2.1). The top level of the nest represents the choice of mode (restricted to HOV vs. SOV in this case). The second level of the nest is the choice of lane/route given the chosen mode. For the HOVs, the choice in this level is between the express (HOV) lane vs. the general (mixed-flow) lane. For the SOVs, the choice is between express (toll) lane vs. the general lane. The bottom nest is the time of day choice that has been split into 1-min intervals relative to the desired “work start” time. The lane choice has been assumed to be analogous to route choice and assumed to be constant over a link.

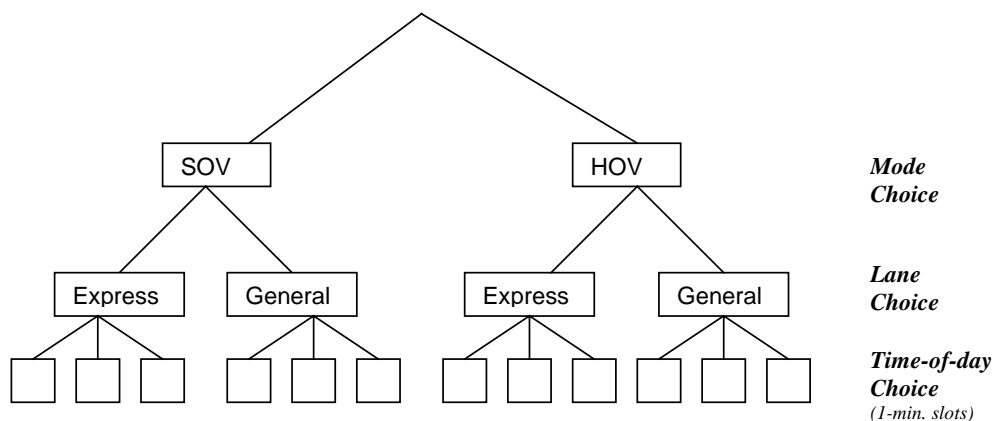


Figure 2.1 - Nested logit model for exclusive lane choice

The utility function for the choice of lane (route) was given by:

$$U_l = C_l + \tau T_l + \phi_l LS_{t,l} \quad (2.3)$$

Where, C_l is the alternate specific constant for lane l . T_l is the toll. τ is the coefficient for toll. $LS_{t,l}$ is the logsum from time-of-day choice level and ϕ_l is the corresponding logsum coefficient.

The utility function for the mode choice level was given by:

$$U_m = C_m + \theta D_m + \omega_m LS_{l,m} \quad (2.4)$$

Where, C_m is the alternate specific constant for mode m . D_m is the delay associated with HOVs. θ is the coefficient for delay. $LS_{l,m}$ is the logsum from the lane-choice nest and ω_m is the corresponding logsum coefficient.

However, no rigorous estimation has been carried out to estimate the parameters of the model. Rather, coefficients from separately estimated mode choice, lane choice and departure time choice models have been combined and calibrated to local scenario.

Benson et al (1989) calibrated an existing HOV model for HOT scenario supplementing it with household surveys and available socio economic data reflecting the local conditions.

2.1.2 Operation Models

Mahmassani et al (2001) identified the limitations of application of discrete choice models to predict HOT lane usage for a proposed development (that is not yet available) since the attributes affecting the choice (e.g. travel time) vary dynamically with the conditions in the system depending upon usage. To address these issues, a dynamic network assignment-simulation methodology is used to provide necessary operational inputs to the mode-choice model. In this model, the choice of whether or not to use the HOT lane depends on a ‘generalized cost’ that is a function of the travel time and travel cost. A sensitivity analysis to various elements affecting the generalized cost was performed in this regard. These elements included HOT lane configurations, pricing levels, carpooling attractiveness, departure time window, and sensitivity of the traveler to generalized cost. The lack of consistent trends have however showed that there is a

complex interaction among lane-access, pricing and mode-choice variables and suggested that the behavioral basis of the methodology needed to be refined.

Kwon et al (2000) developed a macroscopic simulation approach to evaluate unlimited access HOV lane operations in a complex freeway system. The model is based on the simple continuum approach that treats the flows in the HOV and general-purpose lanes separately. The merging and diverging points between these two flows are determined in a deterministic manner based on the assumed lane-changing behavior and geometric configurations. The model is based on the assumption that an HOV driver tries to enter the HOV lane as early as possible after entering the freeway and stays in the HOV lanes as long as possible before taking the required exit. Based on this notion, each entrance or exit ramp of a given freeway is assigned a designated HOV merge or diverge point, whose location is determined considering the minimum distance needed to travel to or from the HOV lane. It is further assumed that the distance needed by HOV drivers to enter an HOV lane from an entrance ramp is proportional to the number of lane-changing operations the HOV drivers need to carry out in non-HOV lane region. This has been expressed mathematically as follows:

$$d = n * L_c \quad (2.5)$$

Where, d = distance needed by HOV drivers to enter/exit an HOV lane from an entrance ramp, n = number of lanes needed to be crossed by HOVs to enter the HOV lane from the entrance ramp, L_c = distance required for each lane-changing operation. The value of the lane-changing parameter, L_c can vary depending on the geometric and traffic conditions for a given freeway. The heterogeneity among drivers was however not taken into consideration in determining L_c . The resulting HOV lane simulation module has been incorporated into the KRONOS freeway simulation software.

Al-Deek et al (2000) developed a discrete-event stochastic object-oriented microscopic Toll Plaza Simulation Model (TPSIM) specifically to evaluate the operational performance of ETC lanes in a toll plaza. The lane selection in this model is driven by the choice of desired tollbooth, which is the tollbooth with the shortest queue that the driver is eligible to use.

2.1.3 Limitations of exclusive lane-choice models

Most of the exclusive lane choice models developed for planning purposes are aggregate demand models based on empirical values obtained from previous researches and do not involve any rigorous estimation of the model parameters. Also, the dynamic variation of the attributes affecting the lane-choice with the conditions in the system cannot be properly addressed with these aggregate level models.

On the other hand, the operational level models address the issues regarding the dynamic variation to some extent, but are based on oversimplified assumptions. Lane changes at any point of time and space are not taken into consideration in any of these models. For example, the exclusive lanes are assumed to have limited entry and exit points. For analyses involving unlimited access exclusive lanes, these entry and exit points are assumed to be at a constant distance away from the on-ramps and off-ramps for the entire driver population and the driver heterogeneity is ignored. Thus, shifts to exclusive lanes are restricted to fixed points and the full flexibility associated with the unlimited access to exclusive lanes is ignored. In some of the operational level models, lane-choice is assumed to be analogous to route-choice.

Thus, the existing exclusive lane-choice models have a higher level of approach and lack the required level of detail for the robust analysis of traffic phenomena in presence of exclusive lanes. On the other hand, as evident from Section 1.3, microscopic traffic simulators, with their capabilities to simulate traffic conditions based on behavior of individual drivers, can be an effective tool to model the dynamic variation in traffic conditions and to perform detailed analyses of traffic situations involving exclusive lanes. These microscopic traffic simulators can accommodate lane-changes at any point of time and space and have detailed driving behavior models that simulate second by second acceleration and lane-changing behavior. Since, the lane-changing behavior is significantly affected by presence of exclusive lanes, the lane-changes models used in the microscopic simulation models are reviewed in the next section to evaluate their validity and applicability in exclusive lane situations.

2.2 Lane-changing models

Lane-changing models have been developed independently as well as jointly with other models like the gap acceptance models and acceleration models.

2.2.1 Lane selection

The first lane-changing model intended for micro-simulation tools was introduced by Gipps (1986). The model considers the necessity, desirability and safety of lane-changes. Drivers' behavior is governed by two basic considerations: maintaining a desired speed and being in the correct lane for an intended turning maneuver. The distance to the intended turn defines which zone the driver is in and which of the considerations are active. When the turn is far away it has no effect on the behavior and the driver concentrates on maintaining a desired speed. In the middle zone, lane-changes will only be considered to the turning lanes or lanes that are adjacent to them. Close to the turn, the driver focuses on keeping the correct lane and ignores other considerations. The zones are defined deterministically, ignoring variation between drivers and inconsistencies in the behavior of a driver over time. When more than one lane is acceptable the conflict is resolved deterministically by a priority system considering locations of obstructions, presence of heavy vehicles and potential speed gain. No framework for rigor estimation of the model's parameters was proposed.

Several micro-simulators implement lane-changing behaviors based on Gipps' model. In CORSIM (Halati et al 1997, FHWA 1998) lane-changes are classified as either mandatory (MLC) or discretionary (DLC). MLC are performed when the driver must leave the current lane (e.g. in order to use an off-ramp or avoid a lane blockage). DLC are performed when the driver perceives that driving conditions in the target lane are better, but a lane-change is not required.

Yang and Koutsopoulos (1996) implemented a rule based lane-changing model in MITSIM where lane changes are classified as MLC and DLC. Drivers perform MLC to connect to the next link on their path, bypass a downstream lane blockage, obey lane-use regulations and respond to lane-use signs and variable message signs. Conflicting goals are resolved probabilistically using utility maximization models. DLC are considered

when the speed of the leader is below a desired speed. The driver then checks the opportunity to increase speed by moving to a neighbor lane.

A similar approach is adapted in SITRAS (Hidas and Behbahanizadeh, 1998) where downstream turning movements and lane blockages may trigger either MLC or DLC, depending on the distance to the point where the lane-change must be completed. In this model, MLC are also performed in order to obey lane-use regulations. DLC are performed in an attempt to obtain speed or queue advantage, defined as the adjacent lane allowing faster traveling speed or having a shorter queue.

Ahmed et al (1996) and Ahmed (1999) developed and estimated the parameters of a lane-changing model that captures both MLC and DLC situations. A discrete choice framework is used to model three lane-changing steps: decision to consider a lane-change, choice of a target lane and acceptance of gaps in the target lane. The model framework is presented in Figure 2.2. When an MLC situation applies, the decision whether or not to respond to it depends on the time delay since the MLC situation arose. DLC is considered when MLC conditions do not apply or the driver chooses not to respond to them. The driver's satisfaction with conditions in the current lane depends on the difference between the current and desired speeds. The model also captures differences in the behavior of heavy vehicles and the effect of the presence of a tailgating vehicle. If the driver is not satisfied with driving conditions in the current lane, neighboring lanes are compared to the current one and the driver selects a target lane. Lane utilities are affected by the speeds of the lead and lag vehicles in these lanes relative to the current and desired speeds of the subject vehicle. A gap acceptance model is used to represent the execution of lane-changes.

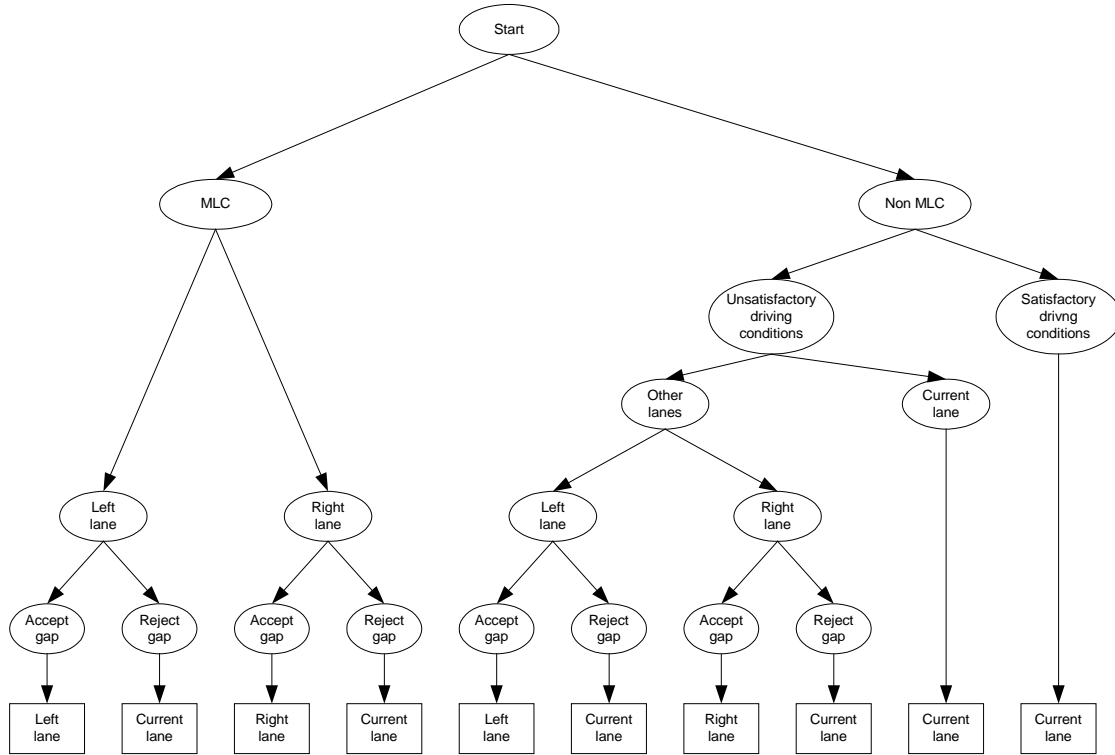


Figure 2.2 - Structure of the Lane-changing Model Proposed by Ahmed (1999)

Ahmed estimated the parameters of this model using second-by-second vehicle trajectory data. The model however does not explain the conditions that trigger MLC situations. The parameters of the MLC and DLC components of the model were estimated separately. The MLC model was estimated for the special case of vehicles merging to a freeway, under the assumption that all vehicles are in MLC state. Gap acceptance models were estimated jointly with the target lane model in each case. The estimation results for DLC and MLC models are summarized in Table 2.1 and Table 2.2 respectively.

Table 2.1 - Estimation results for the DLC model proposed by Ahmed (1999)

Variable	Parameter value
Utility of unsatisfactory driving conditions	
Constant	0.225
(Subject speed - desired speed), m/sec.	-0.066
Heavy vehicle dummy	-3.15
Tailgate dummy	0.423
Utility of left lane	
Constant	-2.08
(Lead speed - desired speed), m/sec.	0.034
(Front speed - desired speed), m/sec.	-0.152
(Lag speed - subject speed), m/sec.	-0.097
Desired speed model	
Average speed, m/sec.	0.768
Lead critical gap	
Constant	0.508
Min (0, lead speed - subject speed), m/sec.	-0.420
$\sigma_{\varepsilon}^{lead,DLC}$	0.488
Lag critical gap	
Constant	0.508
Min (0, lag speed - subject speed), m/sec.	0.153
Max (0, lag speed - subject speed), m/sec.	0.188
$\sigma_{\varepsilon}^{lag,DLC}$	0.526

Table 2.2 - Estimation results for the MLC model proposed by Ahmed (1999)

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

Ahmed (1999) also developed and estimated a forced merging model. This model captures drivers' lane-changing behavior in heavily congested traffic, where acceptable gaps are not available. In this situation, drivers are assumed to change lanes either through courtesy yielding of the lag vehicle in the target lane or by forcing the lag vehicle to slow down. Important factors affecting this behavior include lead relative speed, the remaining distance to the point the lane change must be completed and existence of a total clear gap in excess of the subject vehicle length.

Wei et al (2000) developed a model for drivers' lane selection when turning into two-lane urban arterials. The model captured the effect of the driver's path plan on the lane choice. A set of deterministic lane selection rules were identified based on observations made in Kansas City.

Toledo (2003) developed an integrated lane-changing or lane shift model that allows joint evaluation of mandatory and discretionary considerations. In this model, the relative importance of MLC and DLC considerations vary depending on explanatory variables such as the distance to the off-ramp. This way the awareness to the MLC situation is more realistically represented as a continuously increasing function rather than a step

function. The model consists of two levels: choice of a lane shift and gap acceptance decisions. The structure of the model is shown in Figure 2.3.

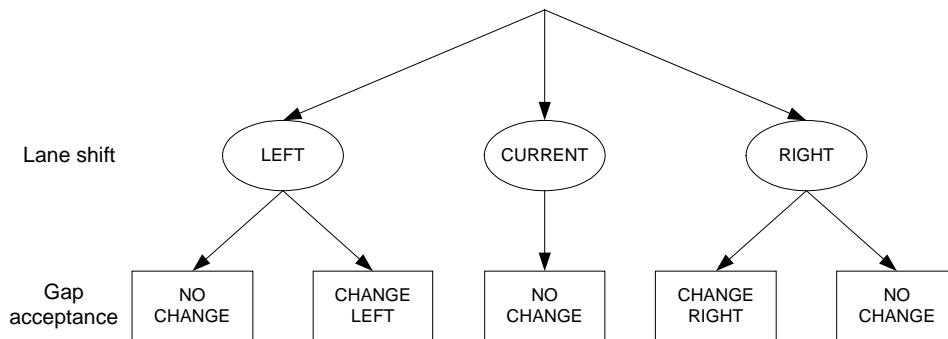


Figure 2.3 - Structure of the lane-changing model proposed by Toledo (2003)

The first step in the decision process is latent since the target lane choice is unobservable and only the driver's lane-changing actions are observed. Latent choices are shown as ovals, observed ones are shown as rectangles. At any particular instance, the driver has the option of selecting to stay in the current lane or opting to move to an adjacent lane. The CURRENT branch corresponds to a situation in which the driver decides not to pursue a lane-change. In the RIGHT and LEFT branches, the driver perceives that moving to these lanes, respectively, would improve his condition in terms of speed and path plan. In these cases, the driver evaluates the adjacent gap in the target lane and decides whether the lane-change can be executed or not. The lane-change is executed (CHANGE RIGHT or CHANGE LEFT) only if the driver perceives that the gap is acceptable, otherwise the driver does not execute the lane-change (NO CHANGE). This decision process is repeated at every time step.

Explanatory variables in Toledo's model include neighborhood variables, path plan variables, network knowledge and experience, and driving style and capabilities. Information about the driver's style and characteristics is however not available and is captured by introducing individual specific error terms.

The parameters of the model were estimated jointly using second by second trajectory data collected in a section of I-395 Southbound in Arlington, VA. The estimation results of the integrated lane-changing model (lane shift model) are summarized in Table 2.3.

Table 2.3 - Estimation results for the lane shift model (Toledo, 2003)

Variable	Parameter value	t-statistic
Shift direction model		
CL constant	2.490	3.74
RL constant	-0.173	-0.51
Right-most lane dummy	-1.230	-3.89
Subject speed, m/sec.	0.062	1.59
Relative front vehicle speed, m/sec.	0.163	3.02
Relative Lag speed, m/sec.	-0.074	-1.30
Front vehicle spacing, m.	0.019	3.42
Tailgate dummy	-3.162	-1.68
Path plan impact, 1 lane change required	-2.573	-4.86
Path plan impact, 2 lane changes required	-5.358	-5.94
Path plan impact, 3 lane changes required	-8.372	-5.70
Next exit dummy, lane change(s) required	-1.473	-2.30
θ^{MLC}	-0.378	-2.29
π_1	0.004	0.46
π_2	0.009	0.77
α^{CL}	0.734	4.66
α^{RL}	2.010	2.73
Lead Critical Gap		
Constant	1.353	2.48
$Max(\Delta V_n^{lead}(t), 0)$, m/sec.	-2.700	-2.25
$Min(\Delta V_n^{lead}(t), 0)$, m/sec.	-0.231	-2.42
α^{lead}	1.270	2.86
σ^{lead}	1.112	2.23
Lag Critical Gap		
Constant	1.429	6.72
$Max(\Delta V_n^{lag}(t), 0)$, m/sec.	0.471	3.89
α^{lag}	0.131	0.64
σ^{lag}	0.742	3.68

2.2.2 Gap acceptance models

Gap acceptance is an important element in most lane-changing models. In order to execute a lane-change, the driver assesses the positions and speeds of the lead and lag vehicles in the chosen lane and decides whether the gap between them is sufficient to execute the lane-change.

Gap acceptance models are formulated as binary choice problems, in which drivers decide whether to accept or reject the available gap by comparing it to the critical gap (minimum acceptable gap). Critical gaps are modeled as random variables to capture the variation in the behaviors of different drivers and for the same driver over time.

In CORSIM, critical gaps are defined through risk factors. The risk factor is defined by the deceleration a driver will have to apply if his leader brakes to a stop. The risk factors to the subject vehicle with respect to the intended leader and to the intended follower with respect to the subject vehicle are calculated for every lane-change. The risk is compared to an acceptable risk factor, which depends on the type of lane-change to be performed and its urgency.

Kita (1993) used a logit model to estimate a gap acceptance model for the case of vehicles merging from a freeway ramp. He found that important factors are the length of the available gap, the relative speed of the subject with respect to mainline vehicles and the remaining distance to the end of the acceleration lane.

Ahmed (1999), within the framework of the lane-changing model described above, assumed that the driver considers the lead gap and the lag gap separately and in order to execute the lane-change, both gaps must be acceptable. Critical gaps are assumed to follow a lognormal distribution in order to guarantee that they are non-negative. Ahmed jointly estimated the parameters of the target lane and gap acceptance models. It was found that lead and lag critical gaps in MLC situations are smaller than those in DLC situations. A similar critical gap approach was used by Toledo in the lane-shift model.

2.3 Limitations of existing models

The literature review on existing lane-changing models reveals that the existing models are all based on the assumption that drivers evaluate the current and adjacent lanes and choose a direction of change (or not to change) based on the relative utilities of these lanes only. The lane choice set is therefore dictated by the current position of the vehicle, and in multi-lane facilities may be restricted to a subset of the available lanes. Thus, existing models lack an explicit tactical choice of a target lane. In reality, the choice of target lane may require a sequence of lane changes from the current lane to this lane. Instead these myopic models can only explain one lane change at a time.

Though the relative evaluation framework may be sufficient to model the lane-changing behavior in conventional freeway situations, it is not suitable for situations where there exists a high difference in LOS among lanes and the driver is free to move to any of the lanes at any instance depending upon gap availability as in the case with exclusive lanes. If a large speed differential prevails among different lanes of the road, drivers are more likely to include all available lanes in their lane-selections and evaluate them based on lane-specific attributes rather than relative evaluation of adjacent lanes. The effects of the lane-specific attributes are more pronounced in presence of exclusive lanes since such lanes can be significantly more attractive compared to other lanes and the drivers may have a very high incentive to move to these lanes. Drivers thus often tend to make multiple lane changes to reach the targeted exclusive lane. However, in existing models since only the adjacent lane is considered for each lane change, the effects of the presence of the exclusive lane may not be captured. To illustrate this, consider the four-lane roadway situation presented in Figure 2.4 where Lane 4 is an HOV lane and the subject vehicle in Lane 2 is eligible to enter the HOV lane. Suppose the HOV lane has significantly higher level of service compared to the other lanes. The lane utilities may be affected by various variables. For simplicity we assume here that the lane utilities are fully captured by the average speed. We further assume that the subject vehicle, vehicle A, is eligible to enter the HOV lane. With existing models, the driver only compares the current lane (Lane 2) to the left lane (Lane 3) and the right lane (Lane 1). Based on the lane speeds in adjacent lanes, Lane 1 is the most desirable of the three and the driver will

change to that lane. However, a more plausible model would be that based on the lane speeds, the driver chooses Lane 4 as the most desirable lane. Thus, from its current position in Lane 2, vehicle A will change to Lane 3 to eventually reach Lane 4.

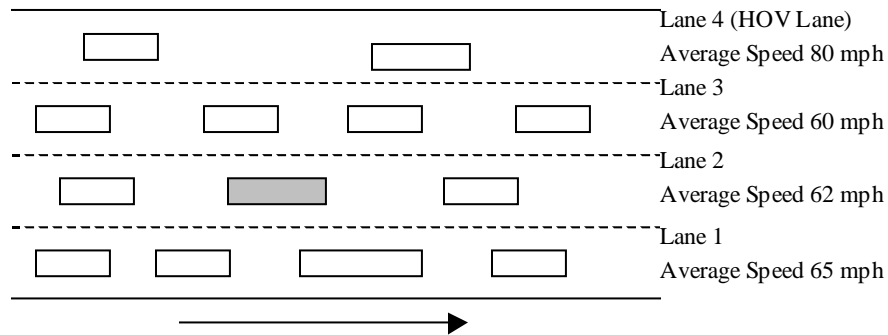


Figure 2.4 - Illustration of myopic behavior in existing lane-changing models

2.4 Summary

It is evident from the literature review that the existing exclusive lane-choice models developed for planning purposes are higher-level models that are useful only in analyzing the exclusive lane usage at an aggregate level. The exclusive lane-choice models at the operational level are based on simplifying assumptions and lack the detailed representation of the driver behavior.

On the other hand, the microscopic simulation tools have detailed driving behavior models, but the existing lane-changing models are all based on the myopic evaluation of the current and adjacent lanes. They do not take into account the effects of the lane-specific variables. Therefore, they are not capable to mimic the lane-changing behavior in presence of exclusive lanes since in such situations there is a high difference in LOS among different lanes and the lane-changing behavior is significantly affected by these lane-specific variables.

Chapter 3

Modeling Framework

The conceptual framework of the proposed lane-changing model is presented in this chapter along with the formulation of the model. The proposed model explicitly introduces the notion of target lane choice as the first step of lane-changing process. This ensures that the model structure is flexible enough to overcome the limitations of the existing myopic lane-changing models.

3.1 The Concept of Target Lane

As revealed from the literature review presented in Chapter 2, an important limitation of existing lane-changing models is that in most cases, the lane-changing behavior is explained only by explanatory variables that capture the attributes of the adjacent lanes, such as the relations between the subject and other vehicles in these lanes. The effects of the lane attributes and vehicle characteristics of lanes further away are not taken into consideration in these models and the lane choice set is dictated by the current position of the vehicle. This shortcoming of existing models is more evident in presence of exclusive lanes where there may be significant differences in the attributes and utilities of the available lanes and a non-adjacent lane may appear to be the most attractive lane to the driver. In such cases the driver may make multiple lane changes to get to his desired lane.

The above discussion demonstrates the need for introducing the concept of target lane choice in the lane-changing model framework to accommodate the influence of attributes of all lanes in the section. The notion of target lane is explained below in this regard.

Target lane is the lane the driver perceives to be the best lane to be in, taking a wide range of considerations into account. These considerations include attributes of the lane, such as the traffic speed and density, as well as well as variables that capture the current

position (lane) of the vehicle, the interactions between the subject vehicle and other vehicles around it, the driver's path plan and driver specific characteristics. According to the target lane concept, a driver may move to a 'worse' adjacent lane as the means of getting to a 'lot better' target lane further away.

The choice of the immediate direction for changing lanes is determined in the direction from the current lane to the chosen target lane, depending on availability of suitable gaps.

3.2 Conceptual Framework

The proposed lane-changing model structure is summarized in Figure 3.1 with examples of a four-lane road.

The model hypothesizes two levels of decision-making: the target lane choice and the gap acceptance. The direction of the driver's immediate lane change is implied by the selected target lane. The driver therefore evaluates the available gaps in that direction. The lane-changing decision process is thus latent, and only the driver's actions (lane changes) are observed. Latent choices are shown as ovals and observed choices are represented as rectangles.

In Figure 3.1, the decision structure shown on the top is for a vehicle that is currently in the second lane to the right (Lane 2) in a four-lane road. Therefore, Lane 3 and Lane 4 are on its left, and Lane 1 is on its right. At the highest level, the driver chooses the target lane. In contrast with existing models the choice set constitutes of all available lanes in the road (Lane 1, Lane 2, Lane 3, Lane 4 in this example). The driver chooses the lane with the highest utility as the target lane. If the target lane is the same as the current lane (Lane 2 in this case), no lane change is required (No Change). Otherwise, the direction of change is to the right (Right Lane) if the target lane is Lane 1, and to the left (Left Lane) if the target lane is either Lane 3 or Lane 4. If the target lane choice dictates a lane change, the driver evaluates the gaps in the adjacent lane corresponding to the direction of change and either accepts the available gap and moves to the adjacent lane (Change Right or Change Left) or rejects the available gap and stays in the current lane (No Change).

The bottom decision structure in Figure 3.1 is for the subject vehicle in Lane 1 in a similar situation.

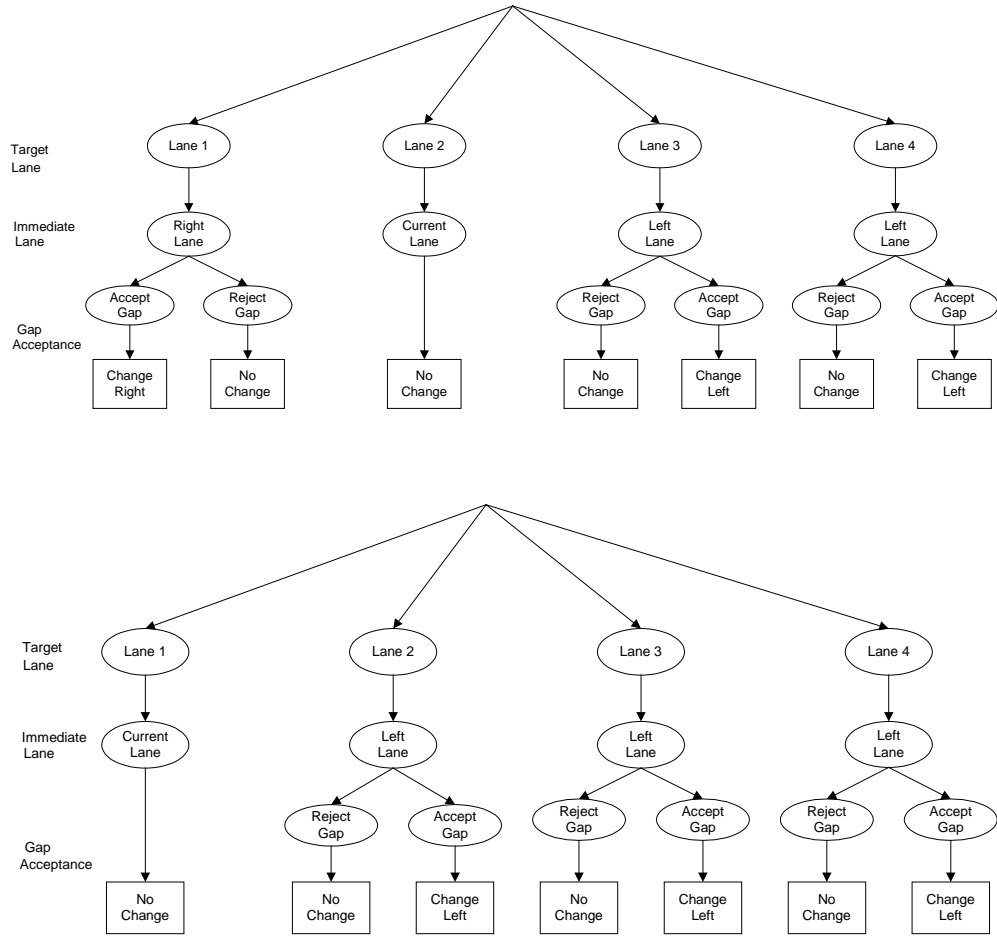


Figure 3.1 - Example of the structure of the proposed lane-changing model

a. For a four-lane road with the subject vehicle in Lane 2

b. For a four-lane road with the subject vehicle in Lane 1

3.3 Model Structure

The lane-changing model explains the choice of the drivers in two dimensions: the target lane choice and the gap acceptance. Furthermore, the estimation data is likely to include repeated observations of drivers' lane-changing choices over a period of time. It is therefore important to capture the correlations among the choices made by a given

driver over time and choice dimensions. However, information about the characteristics of the drivers and their vehicles (e.g. aggressiveness, level of driving skill and the vehicle's speed and acceleration capabilities) is not likely to be included in the data available for model estimation. Therefore, it is necessary to introduce individual-specific latent variables in the various utilities to capture these correlations. It can be assumed that conditional on the value of this latent variable, the error terms of different utilities are independent. This specification is given by:

$$U_{int}^c = \beta^{cT} X_{int}^c + \alpha_i^c \nu_n + \varepsilon_{int}^c \quad (3.1)$$

Where, U_{int}^c is the utility of alternative i in choice dimension c to individual n at time t . X_{int}^c is a vector of explanatory variables. β^c is a vector of parameters. ν_n is an individual-specific latent variable assumed to follow some distribution in the population. α_i^c is the parameter of ν_n . ε_{int}^c is a generic random term with i.i.d. distribution across choices, time and individuals. ε_{int}^c and ν_n are independent of each other.

The resulting error structure (see Heckman 1981, Walker 2001 for a detailed discussion) is given by:

$$cov(U_{int}^c, U_{i'n't'}^{c'}) = \begin{cases} (\alpha_i^c)^2 + \sigma_c^2 & \text{if } n = n', c = c', i = i' \text{ and } t = t' \\ \alpha_i^c \alpha_{i'}^{c'} & \text{if } n = n', c \neq c' \text{ and/or } i \neq i' \text{ and/or } t \neq t' \\ 0 & \text{if } n \neq n' \end{cases} \quad (3.2)$$

σ_c^2 is the variance of ε_{nt}^c .

3.4 Model Components

The specification of the models is discussed below in further detail to explain the two choices drivers make within the lane-changing model: the target lane choice and the gap acceptance decision.

3.4.1 The target lane model

At the highest level of lane-changing, the driver chooses the lane with the highest utility as the target lane. The target lane choice set constitutes of all the available lanes in the roadway.

The total utility of lane i as a target lane to driver n at time t can be expressed by:

$$U_{int}^{TL} = V_{int}^{TL} + \varepsilon_{int}^{TL} \quad \forall i \in TL = \{Lane1, Lane2, Lane3, Lane4\} \quad (3.3)$$

Where, V_{int}^{TL} is the systematic component of the utility and ε_{int}^{TL} is the random term associated with the target lane utilities.

The systematic utilities can be expressed as:

$$V_{int}^{TL} = \beta^{TL} X_{int}^{TL} + \alpha_i^{TL} \nu_n \quad \forall i \in TL = \{Lane1, Lane2, Lane3, Lane4\} \quad (3.4)$$

Where, X_{int}^{TL} is the vector of explanatory variables that affect the utility of lane i . β^{TL} is the corresponding vector of parameters. ε_{int}^{TL} is the random term associated with the target lane utilities. α_i^{TL} is the parameter of individual-specific latent variable ν_n .

The choice of the target lane implies whether or not the current lane of the driver is the most preferred lane and if not, which adjacent lane the driver needs to move to get to the target lane.

The target lane utilities of a driver may be affected by the following:

- Lane attributes
- Surrounding vehicle attributes
- Path plan

General lane attributes, such as the density and speed of traffic in the lane, traffic composition (e.g. percentage of heavy vehicles) etc. can affect the target lane utility. Apart from these, particular lanes may have special lane-specific attributes that enter the utility function of that particular lane. For example, if one of the lanes is a tolled lane, the associated value of toll enters the utility of that specific lane. Similarly, the exclusive lane-specific variables are included in the utility of a lane if the lane in consideration is an exclusive lane. If the driver is eligible to enter the lane, the exclusive lane is likely to have a very high utility for that driver. On the other hand, if the driver is not eligible to

move to a particular lane, a very high disutility is likely to be associated with that particular lane for that specific driver. Thus, for a single occupancy vehicle or SOV, the HOV lane is likely to have a high disutility capturing the penalty associated with moving to that lane violating the law.

The variables associated with the surrounding vehicles, such as speed, spacing and type of the neighboring vehicles may affect the driver's target lane-choice. For example, if the front vehicle in the current lane has a very low speed compared to the driver's desired speed, the current lane is likely to be less preferred by the driver, even if the average speed in that lane is higher than that of the other lanes. It may be noted that the value of these neighborhood variables is denoted by the current position of the vehicle.

The driver usually has a pre-defined destination and schedule (e.g. desired arrival time) for the trip and chooses an appropriate path accordingly. These path plan variables have an important effect on target lane choice. Variables in this group may include distance to a point where the driver needs to be in specific lanes and the number of lane changes required from the target lane to the correct lanes. For example, if the driver is very close to the exit he needs to follow his path, he is less likely to choose a lane further away from the rightmost lane as his target lane.

Thus the systematic utility of a lane can have up to four components at any instant:

- Utility component comprising the generic characteristics of the lane
- Utility component comprising the special characteristics of the lane
- Utility derived from the relative position of the lane with respect to the current lane
- Utility component derived from the path plan of the vehicle

Therefore, the total systematic utility of lane i for individual n at time t can be expressed as follows:

$$V_{int}^{TL} = V_{int}^g + V_{int}^s \delta_i^s + V_{int}^c + V_{int}^p \quad \forall i \in TL = \{Lane1, Lane2, Lane3, Lane4\} \quad (3.5)$$

$\delta_i^s = 1$ if i is a special lane, 0 otherwise.

Where, V_{int}^g is the general systematic utility component of the lane i . V_{int}^s constitutes of special lane-specific utility component and δ_i^s is the indicator of whether or not lane i has that special feature or not. V_{int}^c is the utility component of lane i derived from the current

location c of the vehicle and V_{int}^p is the utility component of lane i derived from the path plan p of the vehicle.

Different choice models are obtained depending on the assumption made about the distribution of the random term ε_{int}^{TL} . Assuming that these random terms are independently and identically Gumbel distributed, choice probabilities for target lane i , conditional on the individual specific error term (v_n) are given by a Multinomial Logit Model:

$$P(TL_{int}^i | v_n) = \frac{\exp(V_{int}^{TL} | v_n)}{\sum_{j \in TL} \exp(V_{int}^{TL} | v_n)} \quad \forall i \in TL = \{Lane1, Lane2, Lane3, Lane4\} \quad (3.6)$$

Where, $V_{int}^{TL} | v_n$ is the conditional systematic utility of the alternative i .

The choice of the target lane dictates the change direction d , if one is required. If the current lane is chosen as the target lane, no change is needed. Otherwise, the change will be in the direction from the current lane to the target lane.

This can be expressed as follows:

$$d = \begin{cases} 1 & \text{if } TL > CL \\ 0 & \text{if } TL = CL \\ -1 & \text{if } TL < CL \end{cases} \quad (3.7)$$

Where, TL and CL are target lane and current indexes.

For example, in Figure 3.1 a, the current lane is Lane 2. If the target lane is Lane 2, no change is needed. If the target lane is Lane 1, $d = -1$ that is a lane change to the right is needed whereas, if the target lane is Lane 3 or Lane 4, $d = 1$ that is a lane change to the left is needed in the immediate time step to get to the target lane.

3.4.2 Gap Acceptance Model

In the target lane model the driver chooses the target lane. The immediate lane-changing is determined as a consequence of the target lane selection. Next, the driver decides whether or not the desired lane change can be undertaken by evaluating the gaps in the corresponding adjacent lane. Conditional on the target lane choice, the gap

acceptance model indicates whether a lane change is possible or not using the existing gaps.

The adjacent gap in the target lane is defined by the lead and lag vehicles in that lane as shown in Figure 3.2. The lead gap is the clear spacing between the rear of the lead vehicle and the front of the subject vehicle. Similarly, the lag gap is the clear spacing between the rear of the subject vehicle and the front of the lag vehicle. Note that one or both of these gaps may be negative if the vehicles overlap.

The driver compares the available lead and lag gaps to the corresponding critical gaps, which are the minimum acceptable space gaps. An available gap is acceptable if it is greater than the critical gap. Critical gaps are modeled as random variables. Their means are functions of explanatory variables. The individual specific error term captures correlations between the critical gaps of the same driver over time. Critical gaps are assumed to follow lognormal distributions to ensure that they are always non-negative:

$$\ln(G_{nt}^{gd,cr}) = \beta^g X_{nt}^{gd} + \alpha^g v_n + \varepsilon_{nt}^{gd} \quad g \in \{lead, lag\}, d \in \{right, left\} \quad (3.8)$$

Where, $G_{nt}^{gd,cr}$ is the critical gap g in the direction of change d , measured in meters. X_{nt}^{gd} is a vector of explanatory variables. β^g is the corresponding vector of parameters. ε_{nt}^{gd} is a random term: $\varepsilon_{nt}^{gd} \sim N(0, \sigma_g^2)$. α^g is the parameter of the driver specific random term v_n .

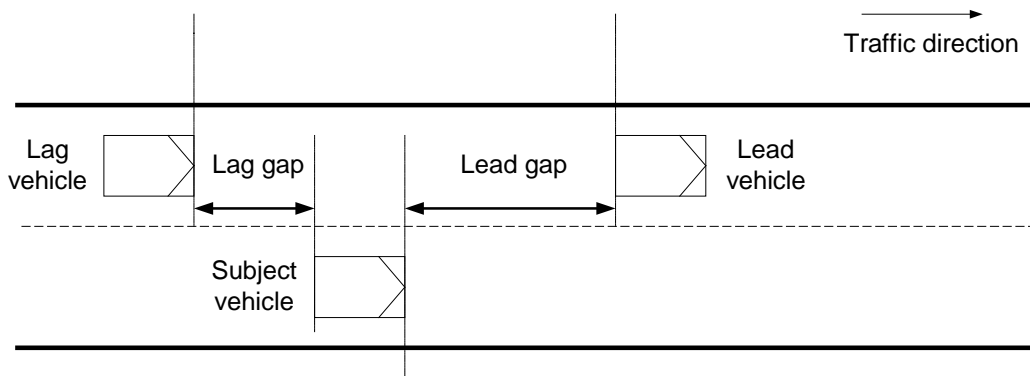


Figure 3.2 - Definitions of the lead and lag vehicles and the gaps they define

The gap acceptance model assumes that the driver must accept both the lead gap and the lag gap to change lanes. The probability of changing lanes, conditional on the individual specific term v_n and the choice of direction of change d_{nt} is therefore given by:

$$\begin{aligned}
P(\text{change in direction } d | d_{nt}, v_n) &= P(l_{nt} = d | d_{nt}, v_n) = \\
P(\text{accept lead gap} | d_{nt}, v_n) &P(\text{accept lag gap} | d_{nt}, v_n) = \\
P(G_{nt}^{lead\ d} > G_{nt}^{lead\ d, cr} | d_{nt}, v_n) &P(G_{nt}^{lag\ d} > G_{nt}^{lag\ d, cr} | d_{nt}, v_n)
\end{aligned} \tag{3.9}$$

$d_{nt} \in \{Right, Current, Left\}$ is the chosen direction of change for driver n at time t , which is implied by the target lane choice. $G_{nt}^{lead\ d}$ and $G_{nt}^{lag\ d}$ are the available lead and lag gaps in this direction, respectively. l_{nt} is the lane-changing action.

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

$$\begin{aligned}
P(G_{nt}^{gd} > G_{nt}^{gd, cr} | d_{nt}, v_n) &= P(\ln(G_{nt}^{gd}) > \ln(G_{nt}^{gd, cr}) | d_{nt}, v_n) = \\
\Phi \left[\frac{\ln(G_{nt}^{gd}) - (\beta^{g^T} X_{nt}^{gd} + \alpha^g v_n)}{\sigma_g} \right] &
\end{aligned} \tag{3.10}$$

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

Gap acceptance is affected by the interaction between the subject vehicle and the lead and lag vehicles in the adjacent lane, which is captured by variables such as the subject relative speed with respect to the lead and lag vehicles.

3.5 Summary

In this chapter, mathematical formulations of the different components of the proposed target lane model have been presented. In this model, the driver selects the lane with the highest utility as his target lane and makes immediate lane changes based on this chosen target lane. A lane change occurs in the direction implied by the chosen target lane depending upon gap availability.

Thus in the target lane model, the choice set of the driver is not limited to the current, right and left lane as in the existing models. Rather, it consists of all lanes in the roadway

section and thus has a stronger behavioral basis. Since, the model explicitly takes into consideration the effects of the lane-specific attributes, as well as neighborhood variables and path plan variables, the proposed model is applicable to all situations including in presence of exclusive lanes.

Chapter 4

Calibration Framework and Data Needs

This chapter gives an overview of the overall calibration framework for the target lane model. The data requirements for estimating, calibrating and validating the model parameters have been summarized in this regard. The process involves two types of data: disaggregate and aggregate. The disaggregate data and the aggregate data have been collected from two separate collection sites. The characteristics of the two datasets are described in this connection.

4.1 Calibration Framework

The process of calibration of the simulation system aims to set the various parameters so that observed traffic conditions are accurately replicated. The overall calibration framework is summarized in Figure 4.1.

The calibration process consists of two steps: initially, the individual models of the simulation are estimated using disaggregate data. Disaggregate data includes detailed driver behavior information such as vehicle trajectories. The required explanatory variables including speeds and relations between the subject vehicle and other vehicles can be generated from the trajectory data. These individual models may be tested independently, for example, using a holdout sample. The disaggregate analysis is performed within statistical software and does not involve the use of a simulation system. The level of effort required to collect and analyze trajectory data and the limited access to modify the models implemented within traffic simulators dictate that this step is most often only performed during the model development.

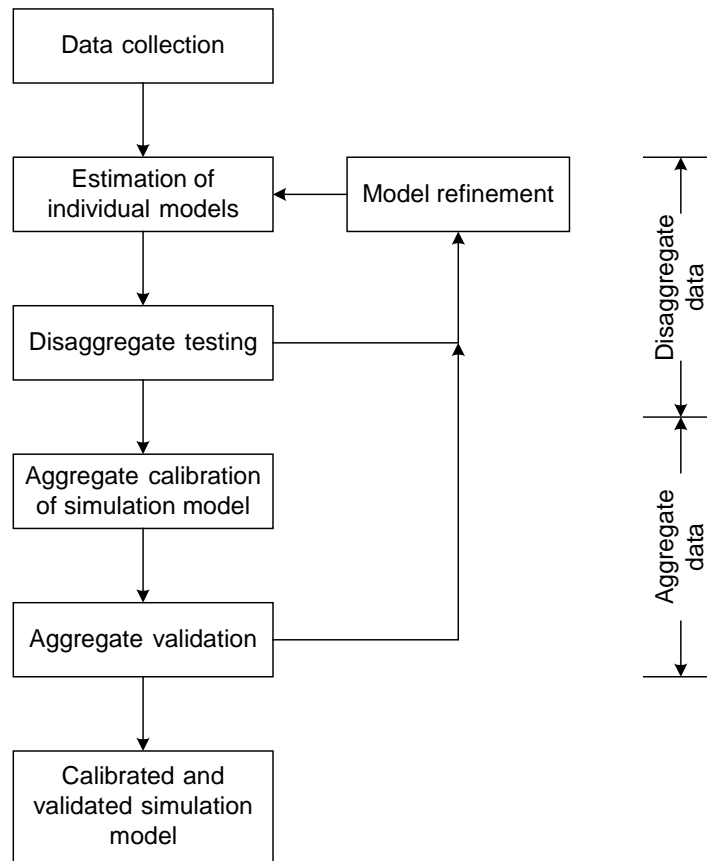


Figure 4.1 - Overall calibration framework

In the second step, the simulation model as a whole is calibrated and then validated using aggregate data like flows, speeds, occupancies, time headways, travel times, queue lengths etc. The process of aggregate calibration of the simulation system aims to adjust the various parameters so that observed traffic conditions are accurately replicated. These parameters consist of the parameters of the behavior model and the travel demand (expressed in terms of origin - destination or OD flows). Also, in special cases, due to limitations of the available disaggregate dataset, it may not be possible to estimate all the parameters of the model in the first step. For example, if the estimation dataset does not have an exclusive lane, it will not be possible to capture the effects of the exclusive lane-specific variables during the estimation step. In such cases, the values of these omitted parameters can be captured during the aggregate calibration.

Once the calibration is complete, the values of the full set of behavioral parameters are fixed and a second set of data is used for validation. Application of the simulation to replicate this dataset also requires OD flows as input. However, these may be different from the ones obtained in the calibration phase and so the OD estimation component of the calibration must be re-done for this dataset. These new OD flows and the calibrated parameter values are used as inputs of the simulation system. During the validation, various goodness of fit statistics may be produced to determine the agreement between the results from the simulation system and the real-world observations. The aggregate calibration and validation steps are detailed in Figure 4.2.

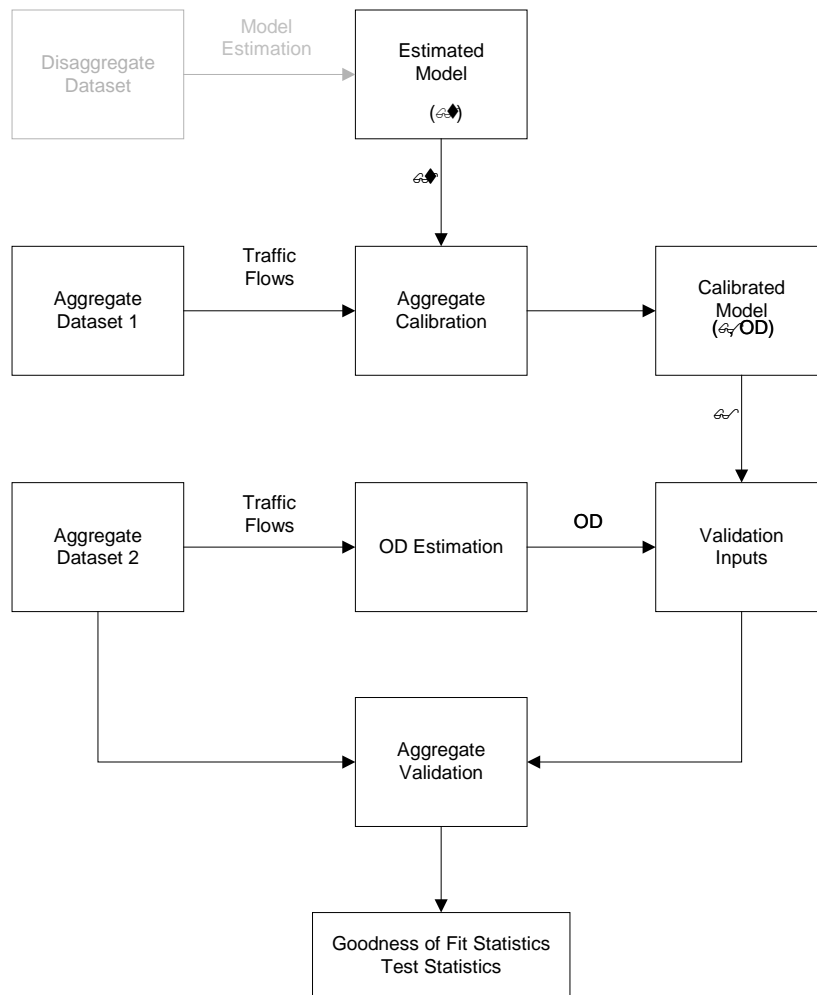


Figure 4.2 - Aggregate calibration and validation of the simulation system

Aggregate calibration and validation are important both in the model development and in its application. In model development, they serve to ensure that the interactions between the individual models within the simulation model are captured correctly. In an application, they are used to refine previously estimated parameter values for the specific site being studied. This is crucial since the driving behavior in the application site may differ largely from the collection site of the data used for model development. In extreme cases, it may be even necessary to introduce new variables in the model before using it in the application site. In such situations, the parameters related to these variables are set during the aggregate calibration process. While this two-step approach is desirable, data availability often dictates what steps are feasible.

4.2 Data Requirements

As mentioned in Section 4.1, disaggregate data is needed in the first step of model development while aggregate data is needed in aggregate calibration and validation.

4.2.1 Disaggregate Data

Detailed disaggregate data is required for model estimation. These include lane-specific variables, neighborhood variables, path plan variables and driver specific attributes. The candidate explanatory variables for the proposed target-lane model are listed below:

- Lane-specific variables: The driver's higher-level lane selection is strongly influenced by the lane-specific variables. These include density and average speed in the lane, out-of-pocket cost associated with the lane if any, distance of the lane with respect to the current lane (indicated by the number of lane changes required to reach the lane), position of the lane in the roadway, special attributes of the lane if any (e.g. exclusive lane or not) etc.
- Adjacent lane variables: These variables describe the subject vehicle and its relations with the vehicles in the neighboring lanes. These include type of the subject vehicle (e.g. heavy vehicle or not), type of neighboring vehicles, relative positions and speeds of the subject vehicle with respect to vehicles surrounding it, geometric elements of the roadway, signals and signs etc.

- Path plan variables: The driver usually has a pre-defined destination and schedule (e.g. desired arrival time) for the trip and chooses an appropriate path accordingly. These path plan variables have an important effect on driving behavior. Variables in this group may include the distance to a freeway off-ramp the driver needs to take (or to turning locations at urban intersections), the number of lane changes required to be in a correct lane to follow the path, indicators to whether or not the driver needs to take the next exit (or turn at the next intersection) and so on.
- Driver specific attributes: The individual driving style, capabilities and preferences of the driver are also likely to affect the lane-changing behavior. These include individual driver/vehicle characteristics, such as the aggressiveness of the driver and driver performance that is related to the network knowledge and experience (e.g. position of on-ramps, experience regarding rightmost lane, position of bus stops, bus traffic and toll plazas etc.).

Trajectory data, which consists of observations of the positions of vehicles at discrete points in time, provides useful information about some of these variables. Trajectory data points are equally spaced in time with short time intervals between them, typically 1 second or less. Speeds, accelerations and lane changes are extracted from the time series of positions. Additional explanatory variables required by the model, such as relations between the subject and other vehicles (e.g. relative speeds, time and space headways, lengths of gaps in traffic) may also be inferred from the raw dataset. The driver specific attributes are however not directly measurable but as discussed in Section 3.3, these characteristics can be captured by introduction of latent variables to capture correlations among different decisions made by the same driver.

4.2.2 Aggregate Data

The aggregate data basically consists of emergent results of the interactions between various behaviors of individual vehicles. These include: traffic flows, speeds and occupancies at sensor locations, travel times, queue lengths, time headways etc. Sources of such data include loop-detectors, aerial photography etc. Aggregate statistics from

trajectory data (e.g. lane-distributions and number of lane changes) can also be used for calibration and validation purposes.

Detailed trajectory dataset involving lane-changes in presence of unlimited access exclusive lanes is not currently available. Therefore, the parameters associated with exclusive lanes in the target lane selection model cannot be captured during the disaggregate model estimation. However, as mentioned in Section 4.1, the parameters associated with the exclusive lane choice can be set during the aggregate calibration process using aggregate data from a site with unlimited access exclusive lane.

4.3 Disaggregate Data

4.3.1 The collection site

The dataset used in this study was collected in 1983 by FHWA in a section of I-395 Southbound in Arlington VA (Figure 4.3). It is one of the longest site for which trajectory data is available. The four-lane highway section is 997 meter long. It includes an on-ramp and two off-ramps. An hour of data at a rate of 1 frame per second was collected through aerial photography of the section. A detailed technical description of the systems and technologies used for data collection and reduction is found in FHWA (1985). The dataset, reduced by Toledo (2002) using the local regression procedure developed by Cleveland (1979) and Cleveland and Devlin (1988), contains observations of the position, lane and dimensions of every vehicle within the section every 1 second.

This dataset is particularly useful for estimation of the proposed lane-changing model since the geometric characteristics of the site, with two off-ramps and an on-ramp, initiate a lot of weaving and lane-changing. Though there are no exclusive lanes, the drivers are free to select the lane with the highest utility as the target lane and make subsequent lane-changes depending on availability of gaps along the stretch of collection site. The ramps within the site provide path plan information for the various vehicles.

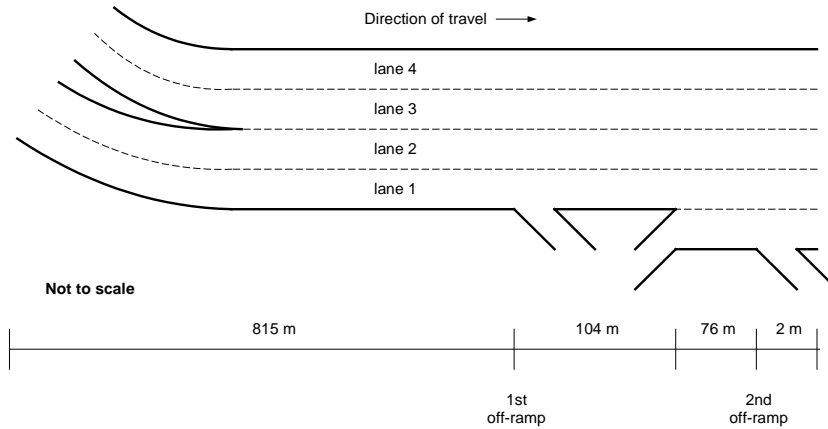


Figure 4.3 - The I-395 data collection site

4.3.2 Characteristics of the disaggregate dataset

The vehicle trajectory data of the various vehicles in the section and the speeds and accelerations derived from these trajectories are used to generate the required variables. The resulting estimation dataset includes 442 vehicles for a total of 15632 observations at a 1 second time resolution. On average a vehicle was observed for 35.4 seconds (observations). All the vehicles are first observed at the upstream end of the freeway section. At the downstream end, the majority of traffic (76%) stays in the freeway. The 8% and 16% of vehicles, which exit the section using the first and second off-ramps (Figure 4.3) respectively, are useful to capture the effect of the path plan on driving behavior.

Lane-specific variables like lane density, lane speed, and percentage of heavy vehicle have been calculated from the raw dataset. The variation of lane-specific variables across the different lanes is summarized in Table 4.1.

Table 4.1 - Variations of Lane-specific Variables

	Lane 1	Lane 2	Lane 3	Lane 4	Segment
Average Density d/s, veh/km/lane	28.41	28.29	28.64	26.56	29.22
Average Density u/s, veh/km/lane	29.86	30.06	30.52	28.29	
Average Speed ,m/sec.	14.22	15.79	16.23	17.50	15.75

The same dataset has been used by Toledo (2002) in estimating the integrated lane-changing model. The detailed characteristics of the dataset documented by Toledo is summarized below:

Speeds in the section range from 0.4 to 25.0 m/sec. with a mean of 15.6 m/sec.. Densities range from 14.2 to 55.0 veh/km/lane with a mean of 31.4 veh/km/lane. The level of service in the section is D-E (HCM 2000). The vehicles the subject interacts with and the variables related to these vehicles are shown in Figure 4.4.

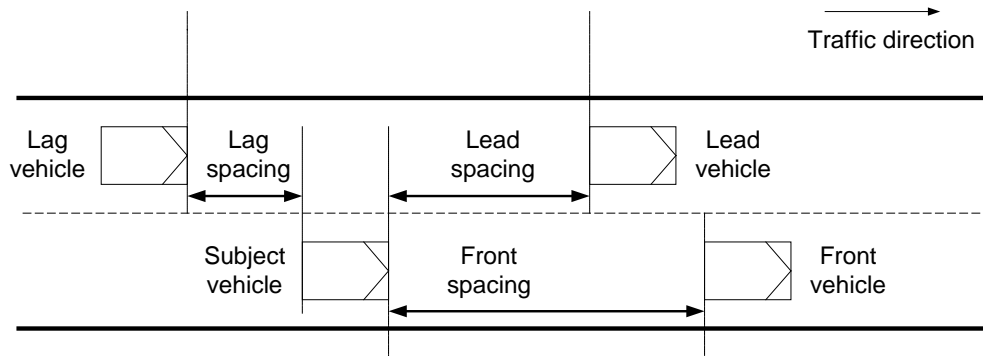


Figure 4.4 - The subject, front, lead and lag vehicles and related variables

Table 4.2 - Statistics of variables related to the subject vehicle and the vehicle in front

Variable	Mean	Std	Medi an	Minimu m	Maxim um
Speed (m/sec)	15.6	3.1	15.8	0.4	25.0
Acceleration (m/sec ²)	0.05	1.21	0.05	-3.97	3.99
Positive	0.96	0.76	0.78	0	3.99
Negative	-0.93	0.75	-0.74	-3.97	0
Density (veh/km/lane)	31.4	6.5	30.8	14.2	55.0
Relations with the front vehicle					
Speed (m/sec)	15.8	3.2	16.0	0.2	25.0
Relative speed (m/sec)	0.2	1.7	0.2	-8.6	9.7
Spacing (m)	26.6	21.2	20.4	1.4	250.5
Time headway (sec)	2.0	1.4	1.7	0.3	27.3

Relative speeds with respect to various vehicles are defined as the speed of these vehicles less the speed of the subject. Table 4.2 summarizes statistics of the variables related to the subject vehicle and the vehicle in front. The distributions of speed, acceleration, density and time headway are shown in Figure 4.5.

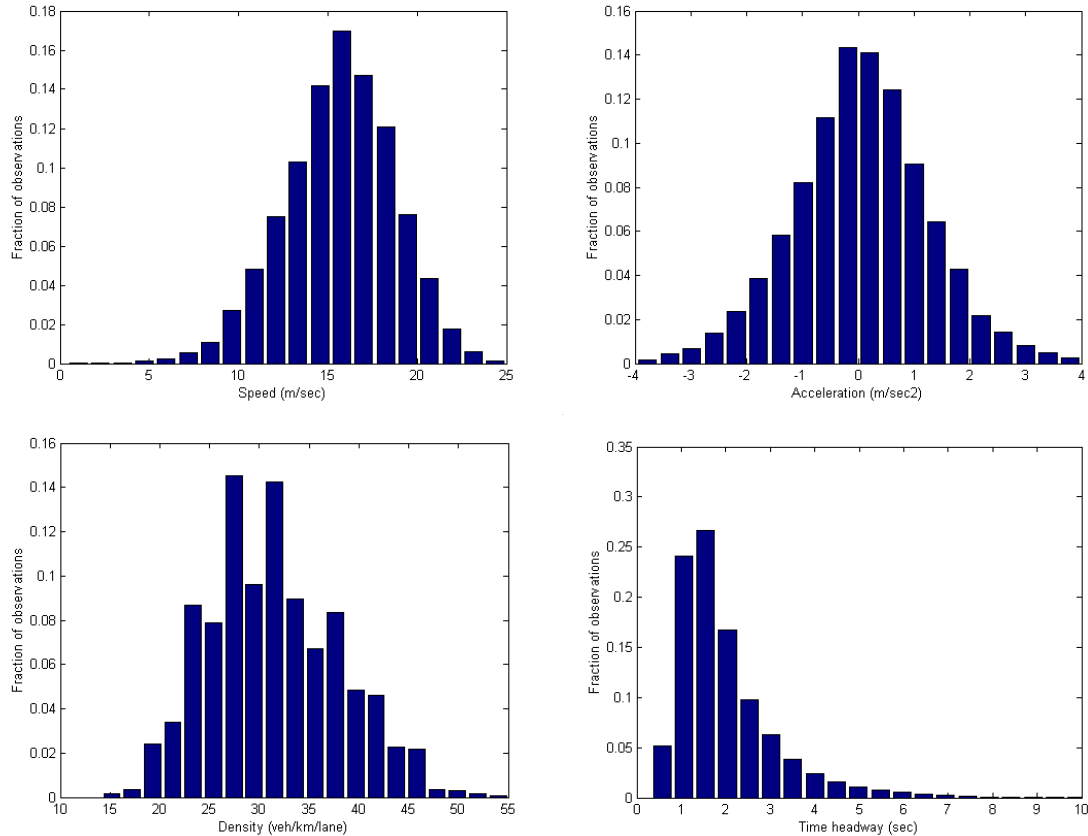


Figure 4.5 - Distributions of speed, acceleration, density and time headway in the data

Lane selection and gap acceptance behaviors are captured by observing lane changes performed by the drivers. An important factor in these behaviors is drivers' desire to follow their path. In this dataset drivers have three possible destinations, each with a corresponding path following behavior:

- Exiting the section through the first off-ramp.
- Exiting the section through the second off-ramp.
- Staying in the freeway at the downstream end of the section.

The distribution of observed lane changes by direction (right, left) and by destination is described in Table 4.3. It is worth noting that many of the vehicles that exit the section through the off-ramps are observed in the right-most lane at the upstream end of the section. This indicates that they may have started considering the path plan constraint

earlier. As a result the coefficients of explanatory variables related to the path plan may be biased towards aggressive behaviors since the more timid drivers are discounted in the dataset.

Table 4.3 - Distribution of lane changes by direction and destination

Destination	Right	Left
Total	123	74
Freeway	71	71
1 st ramp	12	0
2 nd ramp	40	3

Table 4.4 - Statistics describing the lead and lag vehicles

Variable	Mean	Std	Median	Minimum	Maximum
Relations with Lead vehicle					
Relative Speed (m/sec)	0.2 (0.0)	2.6 (2.9)	0.5 (0.1)	-17.3 (-17.5)	8.1 (15.5)
Lead spacing (m)	22.2 (19.6)	21.9 (39.9)	14.1 (13.0)	0.04 (-18.1)	117.9 (268.9)
Relations with Lag vehicle					
Relative Speed (m/sec)	-0.4 (0.0)	2.2 (2.7)	-0.3 (0.0)	-6.7 (-15.0)	5.2 (14.1)
Lag spacing (m)	23.1 (18.6)	20.6 (23.0)	16.6 (12.0)	1.7 (-18.1)	110.1 (232.6)
Statistics are for the accepted gaps only, in parentheses for the entire dataset					

The relations between the subject and the lead and lag vehicles in the adjacent right and left lanes affect the gap acceptance and gap choice behaviors of the driver. Table 4.4 summarizes statistics of the accepted lead and lag gaps (i.e. the gaps vehicle changed lanes into). Accepted lead gaps vary from 0.04 to 117.9 meters, with a mean of 22.2 meters. Accepted lag gaps vary from 1.7 to 110.1 meters, with a mean of 23.1 meters. No significant differences were found between the right and left lanes. Relative speeds are defined as the speed of the lead vehicle or the lag vehicle less the speed of the subject. Statistics for the entire dataset are also shown. With these statistics, negative spacing values indicate that the subject and the lead vehicle partly overlap (this is possible because they are in different lanes). As expected, the mean accepted gaps are larger than

the mean gaps in the traffic stream. Similarly, lead relative speeds in accepted gaps are larger than in the mean of the dataset and lag relative speeds are smaller in the entire dataset (i.e. on average, in accepted gaps the subject vehicle is slower relative to the lead vehicle and faster relative to the lag vehicle compared to the entire dataset). The distributions of relative speeds and spacing, with respect to the front, lead and lag vehicles are shown in Figure 4.6 and Figure 4.7 respectively.

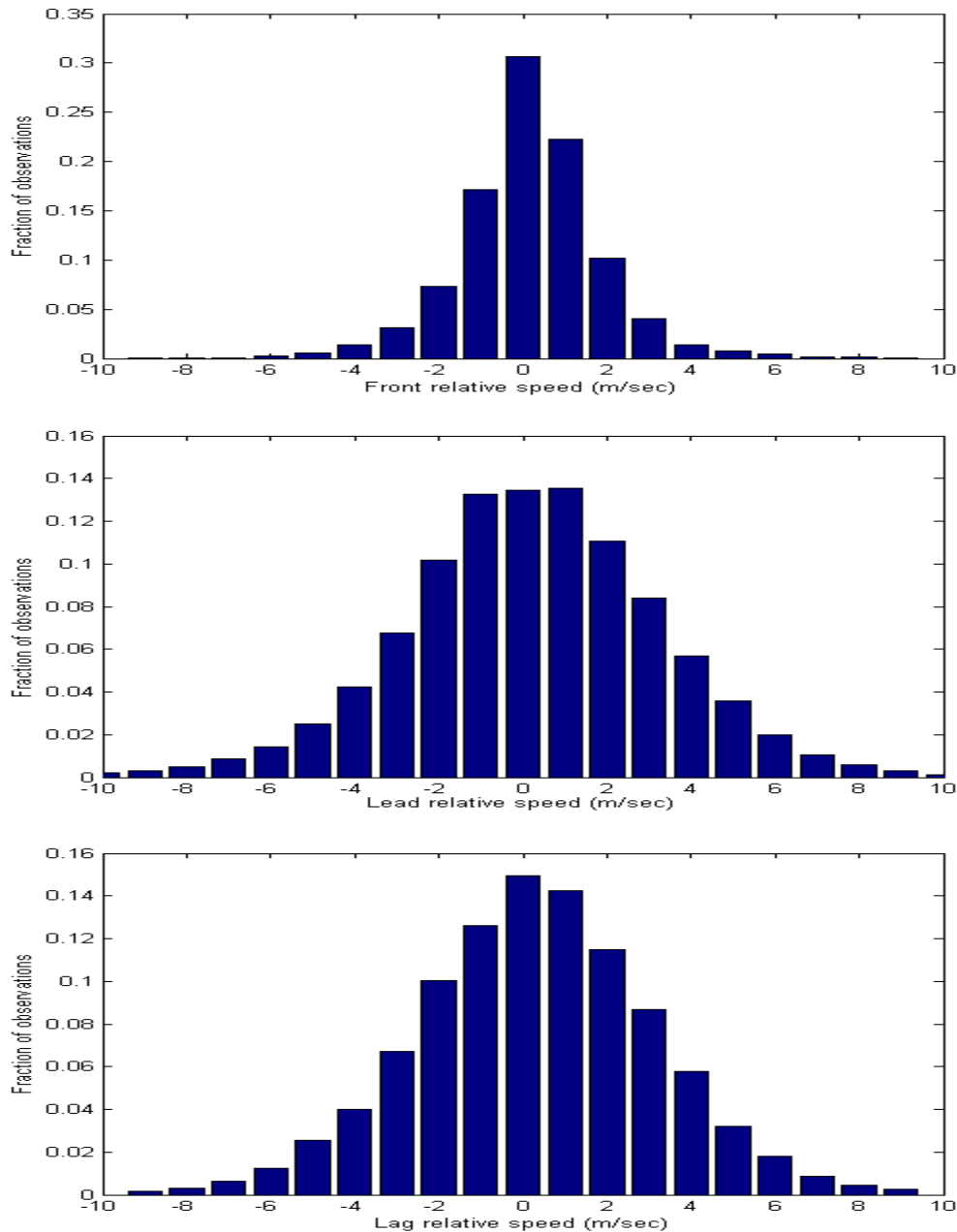


Figure 4.6 - Distributions of relative speed with respect to the front, lead and lag vehicles

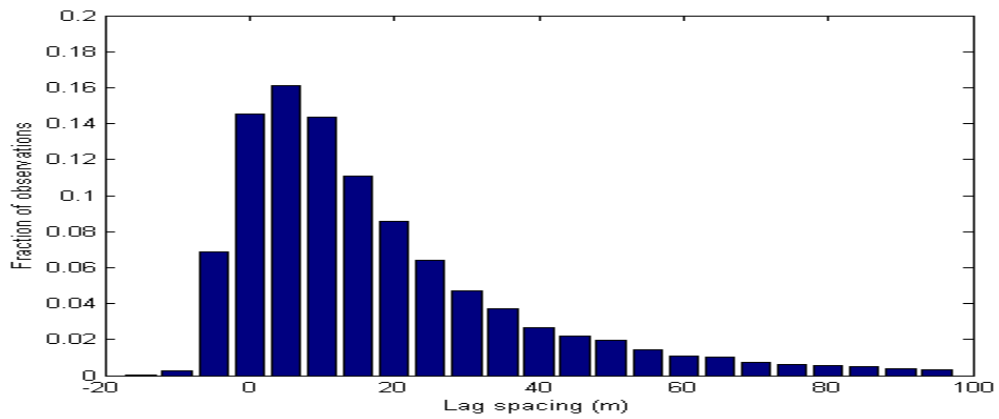
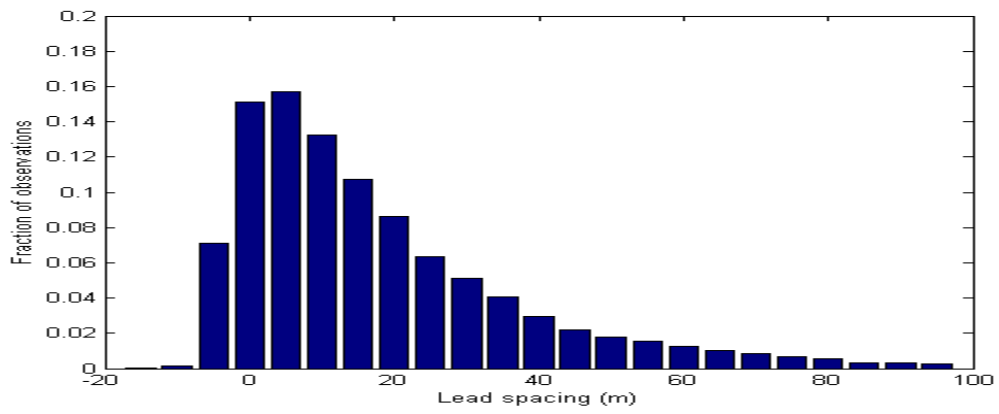
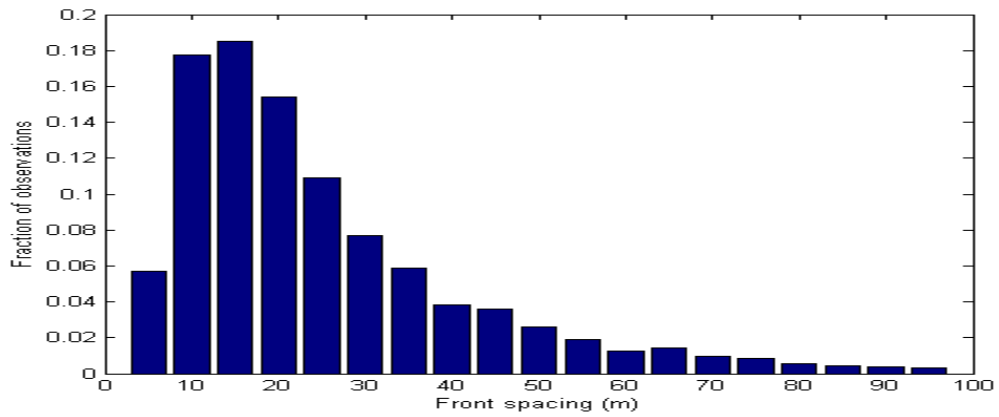


Figure 4.7 - Distributions of spacing with respect to the front, lead and lag vehicles

4.4 Aggregate data

4.4.1 The collection site

The data for aggregate calibration and validation consists of sensor data and aggregate trajectory data. The data collection site includes approximately 1.5 miles of highly congested section of I-80, in Emeryville and Berkeley California, shown schematically in Figure 4.8. This freeway serves approximately 275,000 vehicles daily, and is considered one of the most vital transportation links in the San Francisco Bay Area. South of the study area, I-80 connects to the Bay Bridge and downtown San Francisco, as well as freeway interchanges to I-880 and downtown Oakland, and I-580 East. To the north of the study area are residential East Bay neighborhoods and I-580 West, leading to U.S. 101 and the Marin County. Most of the drivers traveling on this area, often referred to as “the Maze,” are local commuters. The left-most lane is an HOV lane that can be accessed to and exited from at any point in the section. The presence of this unlimited access HOV lane results in high difference in the level of service among different lanes and is therefore useful to test the lane-changing model.

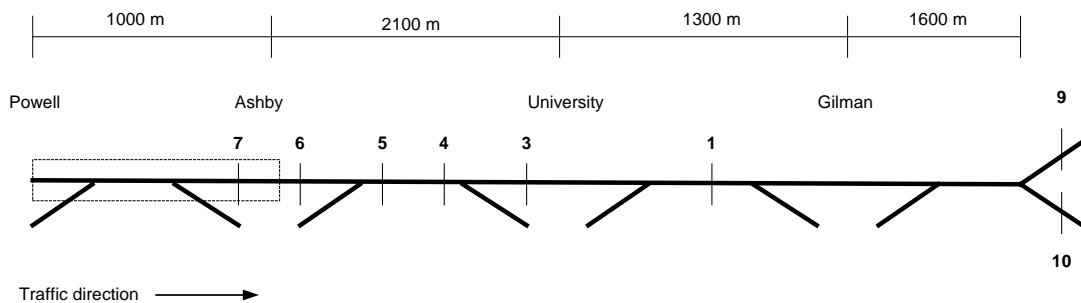


Figure 4.8 - The I-80 validation section

The selected segment includes four on-ramps and three off-ramps. The downstream end of the network extends beyond the I-80/I-580 split, which is the major bottleneck in this area. These boundaries have been selected in order to ensure that possible queues forming at this bottleneck could be captured and explained in the model. The geometry of this section is particularly useful for validation of the lane-changing model for several reasons:

- The presence of the unlimited access HOV lane and the high LOS differential associated with it.
- The section includes weaving sections that are required to test the lane-changing model.
- The multiple ramps that exist in this section provide the ability to verify the lane pre-positioning (“look ahead”) effects that are incorporated in the model.
- The selected network is a corridor and therefore the complex route choice situations do not arise. This is a desirable property for this study since it eliminates route choice as a source of modeling error, and so results would be more indicative of the effect of the driving behavior.

4.4.2 Characteristics of the dataset

The data for aggregate calibration and validation consist of sensor data at the locations shown schematically in Figure 4.8. The data is available for two weeks (10 weekdays) at 30-second intervals. The data set includes lane-specific traffic counts, occupancies and speeds. The time dependent traffic counts and speeds are shown in Figure 4.9 and Figure 4.10, respectively. In addition trajectory data from the part of the corridor between the Powell Street and Ashby Street interchanges (showed by a dotted rectangular in Figure 4.8) is also available for one day between 2.35PM and 3.05PM. Aggregate statistics derived from these trajectories, which provide richer information compared to the sensor data, are also used in the validation. The available sensor data has been split in two data sets with one week of data in each. The first week of data is used for aggregate calibration of the MITSIMLab model (as discussed later in Section 6.2). The second week of data is used only for validation of the calibrated model and therefore allows independent validation (as discussed later in Section 6.3). The calibration phase focuses on the time period 2.30PM-6PM, which encompasses the peak period in this section.

**Average Counts
(Vehicle/15 Minutes)**

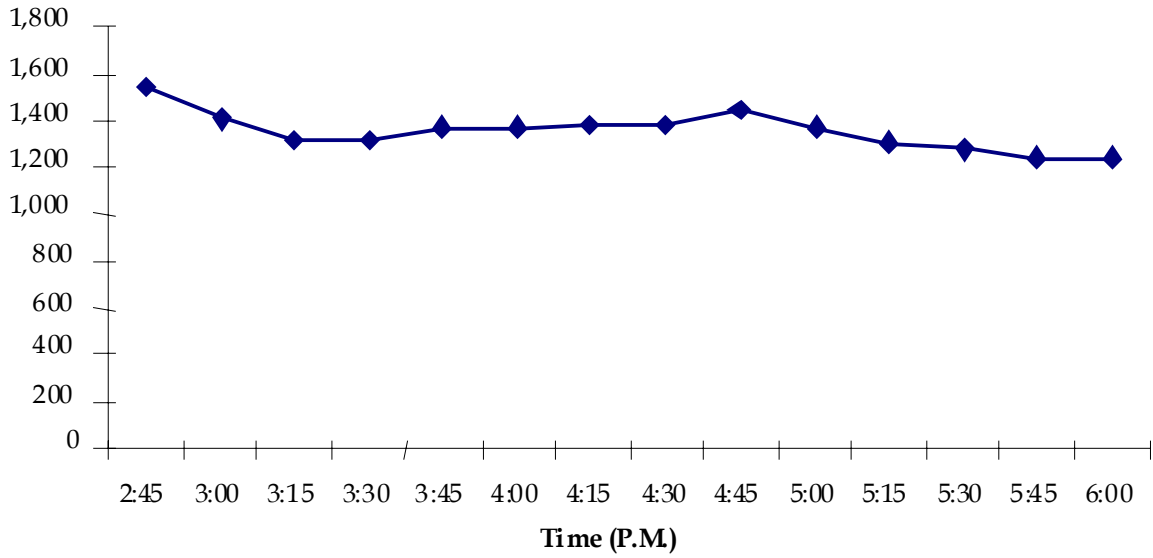


Figure 4.9 - Time dependent traffic counts in the sensor data

Speed (Miles Per Second)

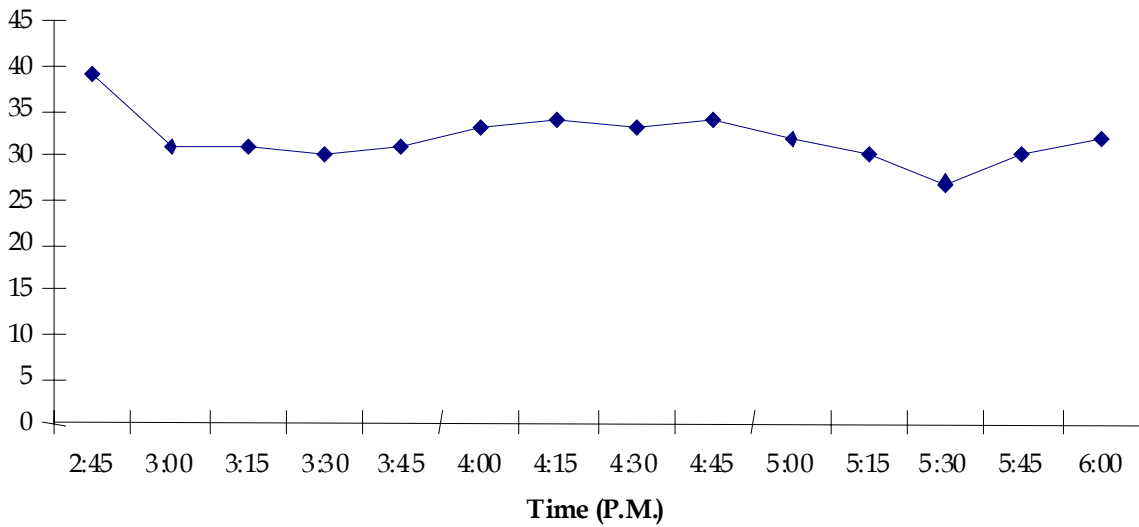


Figure 4.10 - Time dependent traffic speeds in the sensor data

Since several freeway corridors meet near the collection site, heavy weaving maneuvers are observed in this area. The presence of the unlimited access HOV lane also leads to occurrence of special type of lane-changes. This is also observed from the aggregate trajectory data as summarized in Table 4.5 and Table 4.6.

Table 4.5 - Percent end lane distribution by starting lane

2:35 – 2:50 PM							
Starting Lane	Ending Lane						
	1	2	3	4	5	Ashby Off	Total
1	86%	11%	3%	0%	0%	0%	100%
2	13%	72%	11%	4%	1%	0%	100%
3	4%	20%	59%	11%	2%	3%	100%
4	2%	16%	29%	43%	3%	7%	100%
5	1%	6%	18%	36%	32%	8%	100%
6	0%	1%	3%	15%	54%	27%	100%
Powell On	1%	4%	11%	28%	52%	4%	100%
2:50 – 3:05 PM							
Starting Lane	Ending Lane						
	1	2	3	4	5	Ashby Off	Total
1	90%	8%	2%	0%	0%	0%	100%
2	10%	75%	10%	3%	1%	1%	100%
3	6%	24%	49%	16%	3%	3%	100%
4	3%	12%	29%	42%	7%	7%	100%
5	5%	4%	14%	32%	33%	12%	100%
6	1%	0%	4%	11%	49%	35%	100%
Powell On	3%	2%	13%	29%	49%	4%	100%

Table 4.6 - Average lane changes by starting lane

Time	Starting Lane							Powell On	Avg. by period
	1	2	3	4	5	6			
2:35 - 2:50 PM	0.24	0.43	0.79	1.00	1.14	0.85	1.68	0.74	
2:50 - 3:05 PM	0.17	0.39	0.91	1.04	1.26	0.74	1.72	1.45	
Average by starting lane	0.21	0.41	0.86	1.03	1.21	0.80	1.70	0.79	

The spatial distribution of vehicles in different lanes, as observed in the trajectory data, is summarized in Figure 4.11.

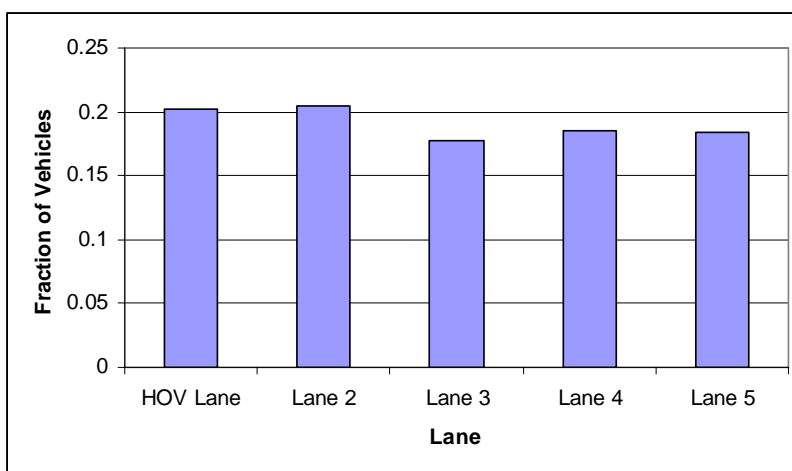


Figure 4.11 - Spatial distribution of vehicles in lanes derived from trajectory data

4.5 Summary

In this chapter, the framework for calibration of the lane-changing model has been outlined. The data requirements for the estimation, calibration and validation have been discussed in this regard.

Trajectory data, which consists of observations of the positions of vehicles at discrete points in time, can be used in estimating the model parameters. Aggregate data (e.g. sensor counts and speeds) can be used for calibrating and validating the model after it has been implemented in a simulator. In special cases, it may not be possible to capture the effects of all variables with the available trajectory data. In such cases, the omitted parameters (that are uncaptured in the disaggregate estimation step) are captured during the calibration process.

The characteristics of the collection site for the disaggregate and the aggregate data used to calibrate the target lane model have been summarized in this chapter. In this case, trajectory data from I-395 Arlington, VA will be used to estimate the model parameters. Since there are no exclusive lanes in this section, the exclusive lane-specific utility component cannot be included during the estimation. The model however can have a generalized structure that can accommodate the generic target lane choice. The model parameters will be calibrated with aggregate data (sensor counts and speeds from I-80 in this case) using simulation runs. The parameters of the exclusive lane-specific utility component can be captured during the aggregate calibration of the model. The calibrated model (with exclusive lane-specific parameters) can be validated with a different set of aggregate data (aggregate trajectory data and sensor counts and speeds from I-80 in this case).

Chapter 5

Estimation

The estimation results of the proposed lane-changing model using the Arlington, VA dataset are presented in this chapter. Both lane-selection and gap-acceptance components of the model have been estimated jointly using a maximum likelihood estimation procedure. The likelihood function for this joint estimation, based on the available data, is formulated first. The estimation results are presented next. A discussion on the estimation results is presented after that in the hierarchical order of the hypothesized decision-making process: the target lane model is presented first, followed by the gap acceptance model. Statistical tests confirming the superiority of the target-lane model over the integrated lane-changing model based on myopic lane shift (Toledo 2003) has been presented in the end.

5.1 Likelihood Function

In this section, the likelihood function of lane-changing actions observed in the data is presented. Important explanatory variables affecting the target lane choice are those related to the path-plan. However, when studying a section of road, this information is not likely to be observed for some of the vehicles (e.g. vehicles exiting a freeway downstream of the section observed). In order to capture the effect of these variables, a distribution of the distances from the downstream end of the road section being studied to the exit points is used. The alternatives considered are the first, second and subsequent exits. The probability mass function of the distance beyond the downstream end of the section to the off-ramps used by drivers is given by:

$$p(s_n) = \begin{cases} \pi_1 & \text{first downstream exit } (s^1) \\ \pi_2 & \text{second downstream exit } (s^2) \\ 1 - \pi_1 - \pi_2 & \text{otherwise } (s^3) \end{cases} \quad (5.1)$$

Where, π_1 and π_2 are parameters to be estimated. s^1 , s^2 and s^3 are the distances beyond the downstream end of the section to the first, second and subsequent exits, respectively.

The first and second exit distances (s^1 and s^2) are measured directly. For the subsequent exits an infinite distance is used ($s^3 = \infty$). This corresponds to an assumption that while on the section being studied, drivers that use these exits ignore path-plan considerations. The parameters of this distribution are estimated jointly with the other parameters of the model.

The joint probability density of a combination of target lane (TL) and lane action (l) observed for driver n at time t , conditional on the distance to the exit point, s_n , and the individual-specific characteristic, ν_n is given by:

$$P(TL_{nt}^i, l_{nt} | s_n, \nu_n) = P(TL_{nt}^i | s_n, \nu_n) P(l_{nt} | TL_{nt}^i, \nu_n) \quad (5.2)$$

$P(TL_{nt}^i | \cdot)$ and $P(l_{nt} | \cdot)$ are given by Equations (3.6) and (3.10), respectively.

Only the lane-changing actions are observed. The marginal probability of the lane-action is therefore given by:

$$P(l_{nt} | s_n, \nu_n) = \sum_{j \in TL} P(TL_{nt}^j, l_{nt} | s_n, \nu_n) \quad (5.3)$$

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

$$P(l_n | s_n, \nu_n) = \prod_{i=1}^{T_n} \sum_{j \in TL} P(TL_{nt}^j, l_{nt} | s_n, \nu_n) \quad (5.4)$$

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

$$L_n = \int \sum_s P(l_n | s, \nu) p(s) f(\nu) \quad (5.5)$$

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

$$L = \sum_{n=1}^N \ln(L_n) \quad (5.6)$$

The maximum likelihood estimates of the model parameters are found by maximizing this function. In this study, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization algorithm implemented in the statistical estimation software GAUSS (Aptech Systems 1994) has been used. BFGS is a quasi-Newton method, which maintains and updates an approximation of the Hessian matrix based on first-order derivative information (see, for example, Bertsekas 1999). GAUSS implements a variant of BFGS due to Gill and Murray (1972), which updates the Cholesky decomposition of the Hessian (Aptech Systems 1995).

The integrals in the likelihood function were calculated numerically using the Gauss-Legendre quadrature method (Aptech Systems 1994). Numerical integration is expected to perform better than Monte-Carlo integration in the application at hand because of the presence of the reaction time dimension: Monte-Carlo integration would require explanatory variable values, lagged by the reaction time, to be calculated for each draw. In contrast, with numerical integration only the explanatory variables values for the (much fewer) points used for the integration need to be calculated.

The likelihood function is not globally concave. For example, if the signs of all the coefficients of the individual-specific error term are reversed, the solution is unchanged due to its symmetric distribution function. To avoid obtaining a local solution, different starting points have been used in the optimization procedure.

5.2 Estimation Results

The estimation results of the proposed lane-changing model with the data from I-395 section are presented in Table 5.1.

Table 5.1 - Estimation results of the target lane model

Variable	Parameter value	t-statistic
Target Lane Model		
Lane 1 constant	-1.696	-3.03
Lane 2 constant	-0.571	-1.68
Lane 3 constant	0.059	1.16
Lane density, vehicle/km	-0.013	-1.21
Average speed in lane, m/sec	0.176	1.59
Front vehicle spacing, m.	0.024	3.86
Relative front vehicle speed, m/sec.	0.115	1.46
Tailgate dummy	-4.935	-1.96
CL dummy	2.686	1.55
1 lane-change from the CL	-0.845	-1.15
Each additional lane-change from the CL	-3.338	-1.91
Path plan impact, 1 lane change required	-2.549	-4.57
Path plan impact, 2 lane changes required	-4.953	-2.19
Path plan impact, 3 lane changes required	-6.955	-1.65
Next exit dummy, lane change(s) required	-0.872	-1.35
θ^{MLC}	-0.417	-2.48
π_1	0.001	0.68
π_2	0.086	1.38
α^{lane1}	-1.412	-2.29
α^{lane2}	-1.072	-0.50
α^{lane3}	-0.071	-3.61
α^{lane4}	-0.089	-1.56

Lead Critical Gap		
Variable	Parameter value	t-statistic
Constant	1.541	5.59
$Max(\Delta S_{nt}^{lead}, 0)$, m/sec.	-6.210	-3.60
$Min(\Delta S_{nt}^{lead}, 0)$, m/sec.	-0.130	-2.09
α^{lead}	-0.008	-3.17
σ^{lead}	0.854	1.29
Lag Critical Gap		
Constant	1.426	5.35
$Max(\Delta S_{nt}^{lag}, 0)$, m/sec.	0.640	3.36
α^{lag}	-0.205	-0.48
σ^{lag}	0.954	4.80
Number of drivers = 442	$L(0) = -1434.76$	
Number of observations = 15632	$L(\hat{\beta}) = -875.81$	
Number of parameters = 31	$\bar{\rho}^2 = 0.368$	

5.2.1 The Target Lane Model

All four classes of variables discussed in Section 4.2, namely lane-specific variables, adjacent lane variables, path plan variables and driver specific attributes, affect target lane choices.

The estimated values of the lane-specific constants imply that, everything else being equal, the right-most lane is the most undesirable. This may be the result of drivers' preference to avoid the merging and weaving activities that take place in that lane. In general, lanes that are more to left are more desirable. However, lanes 3 and 4 have non-negative constants, which may indicate that the advantage of being away from the slower right lanes is balanced by the disadvantage associated with being in lanes that are further away from the off-ramp, and by the increased interaction with vehicles traveling at higher speeds. The results indicate that drivers are more likely to choose lanes with higher average speeds and lower densities, which are intuitive too.

Some of the lane-specific variables are dependent on the current lane of the vehicle. For example, the required maneuver to reach a specific lane is a function of the distance of the lane from the current lane of the driver. The values of the coefficients of the number of lane changes required from the current lane to the target lane denote the disutility associated with choosing target lanes that require lane-changing maneuvers. This has been modeled as a step function and the results indicate that the disutility associated with each additional lane change is much higher when more than one lane-changing maneuver is associated. The coefficient of the current lane dummy captures the inertia preference to stay in the current lane. As expected, the sign of this coefficient is positive. As apparent in Figure 5.1, the lane-specific part of the utility thus changes depending upon the current position of the vehicle, being the highest for the current lane and diminishing with the distance from the current lane.

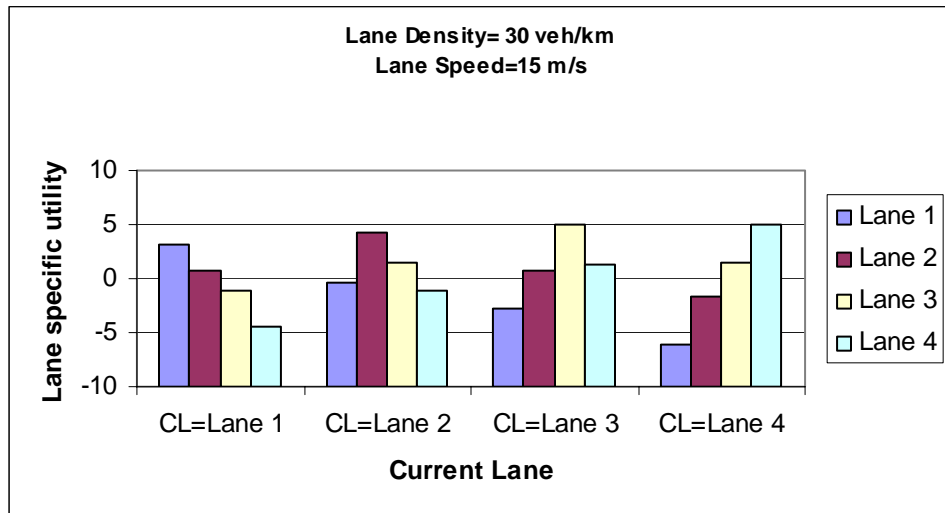


Figure 5.1 - Variation of lane utilities depending on the current lane of the driver

The interactions between the subject vehicle and the vehicles in front of it in the current and adjacent lanes, also affect the target lane choice. Results show that lane utilities increase with the relative front speed and the spacing between the vehicles. The tailgating dummy variable, which captures the presence of a tailgating vehicle behind the subject in its current lane has been found important both in the magnitude of its

contribution to the utility and in its statistical significance. This variable thus captures drivers' strong preference to avoid tailgating situations.

The path plan impact variables indicate that the utility of a lane decreases with the number of lane-changes the driver needs to perform in order to maintain the desired path. This effect is magnified as the distance to the off-ramp (d_{ni}^{exit}) decreases. This has been captured by the negative power of the distance to the off-ramp ($\theta^{MLC} = -0.417$) that guarantees that at the limits, the path-plan impact approaches 0 when $d_{ni}^{exit} \rightarrow +\infty$ and approaches $-\infty$ when $d_{ni}^{exit} \rightarrow +0$. The disutility associated with being in a wrong lane is larger when the driver needs to take the next exit. Figure 5.2 shows the impact of path plan lane-changes on the utility of a lane as a function of the distance from the off-ramp.

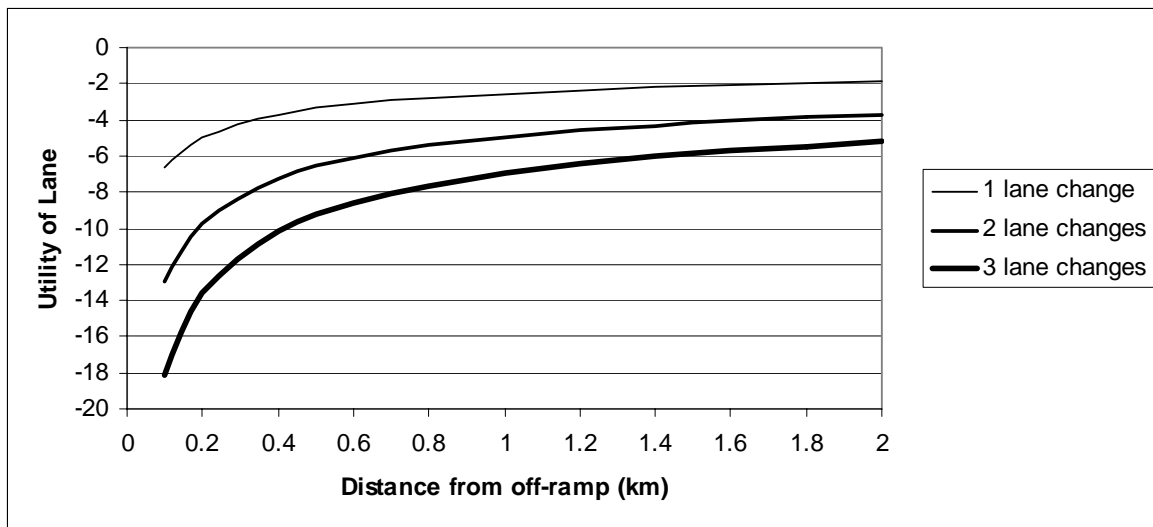


Figure 5.2 - Impact of path plan lane changes on the utility of a lane

The combined effect of path plan and lane-specific attributes is shown in Figure 5.3. It is interesting to note how the utility of each lane is affected by the path plan of the driver. When the driver is very far from his desired exit, the lane utilities are affected primarily by the position of the lane with respect to the current lane of the driver (Figure 5.3a). As the distance to exit decreases, the disutility of being in a lane far from exit becomes more and more pronounced and the relative utility of the lanes in the direction of the exit (right in the example) gradually increase. When the driver is very close to the

exit the path plan effect clearly dominates (Figure 5.3c) and the lanes far from the exit have a very high disutility.

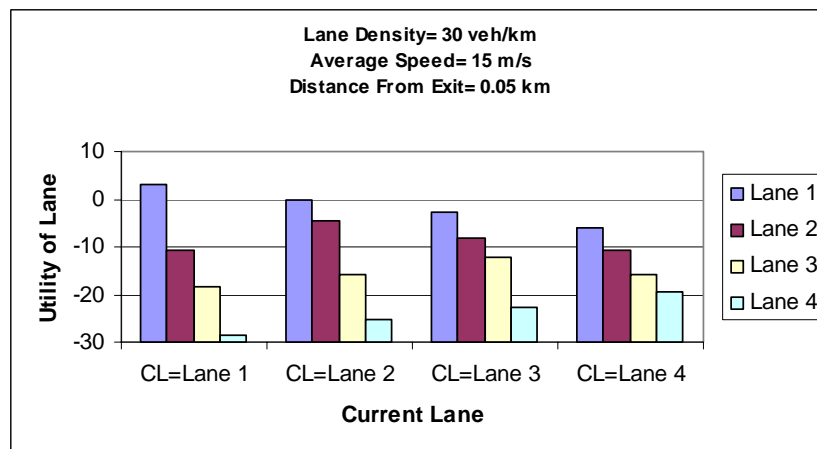
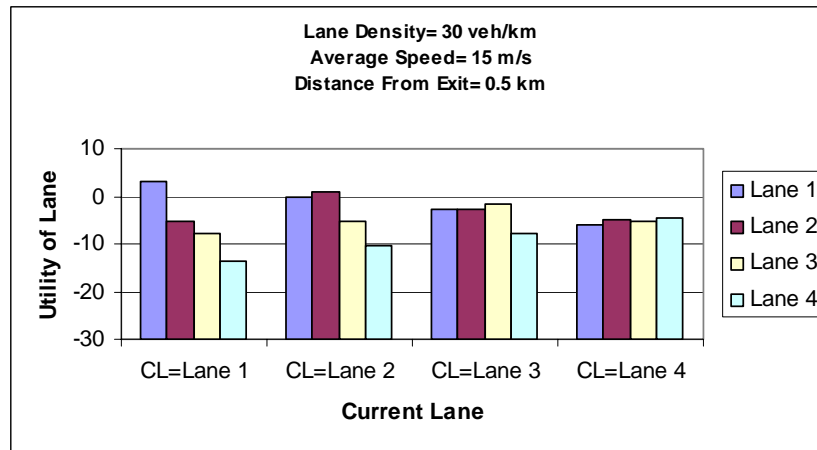
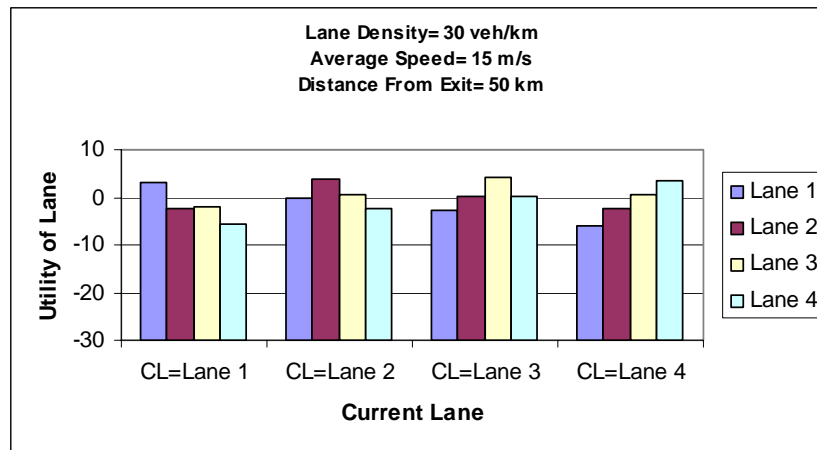


Figure 5.3 - Combined effects of path plan and lane-specific attributes on the utility of a lane
a. Distance from exit=50 km b. Distance from exit=0.5 km c. Distance from exit=0.05 km

The heterogeneity coefficients, α^{lane1} , α^{lane2} , α^{lane3} and α^{lane4} capture the effects of the individual-specific error term v_n on the target lane choice. α^{lane1} and α^{lane2} are more negative compared to α^{lane3} and α^{lane4} . Hence, v_n can be interpreted as correlated with aggressiveness since aggressive drivers are less likely to choose the right lanes over the left ones compared to more timid drivers.

In summary, the target lane utility can be given by:

$$\begin{aligned}
U_{nt}^i = & \beta^i - 0.013D_{nt}^i + 0.176S_{nt}^i + 0.024\Delta X_{nt}^{i,front} \delta_{nt}^{i,CL} + 0.115\Delta S_{nt}^{i,front} \delta_{nt}^{i,adj/CL} \\
& - 4.935\delta_{nt}^{tailgate} \delta_{nt}^{i,CL} + 2.686\delta_{nt}^{i,CL} - 0.845\delta_{nt}^{i,\Delta CL=1} - 3.338(\Delta CL_{nt}^i - 1)\delta_{nt}^{i,\Delta CL>1} \\
& + \left[d_{nt}^{exit} \right]^{-0.417} (-2.549\delta_n^{i,1} - 4.953\delta_n^{i,2} - 6.955\delta_n^{i,3}) - 0.872\delta_{nt}^{next\ exit} \Delta Exit^i \\
& - \alpha^i v_n + \varepsilon_{nt}^i
\end{aligned} \tag{5.7}$$

Where, β^i is the lane i constant. D_{nt}^i and S_{nt}^i are the lane-specific densities and speeds, respectively. $\Delta X_{nt}^{i,front}$ and $\Delta S_{nt}^{i,front}$ are the spacing and relative speed of the front vehicle in lane i , respectively. $\delta_{nt}^{i,adj}$ is an indicator with value 1 if i is the current or an adjacent lane, and 0 otherwise. Similarly, $\delta_{nt}^{i,CL}$ has value 1 if i is the current lane, and 0 otherwise. $\delta_{nt}^{tailgate}$ is an indicator with value 1, if vehicle n is being tailgated at time t and 0 otherwise. ΔCL_{nt}^i are the number of lane changes required to get from the current lane to lane i . $\delta_{nt}^{i,\Delta CL=1}$ and $\delta_{nt}^{i,\Delta CL>1}$ are indicators that have values 1 if the lane i involves one lane change from the current lane and more than one lane changes from the current lane respectively and 0 otherwise. $\beta^{i,path}$ is the path plan impact coefficient for lane i . d_{nt}^{exit} is the distance to the exit driver n intends to use. $\delta_n^{i,1}$ is an indicator with value 1 if lane i is 1 lane away from the desired exit of individual n , 0 otherwise. Similarly, $\delta_n^{i,2}$ and $\delta_n^{i,3}$ are indicators with value 1 if lane i is two and three lanes away from the desired exit of individual n respectively. $\delta_{nt}^{next\ exit}$ is an indicator with value 1 if the driver intends to take the next exit and 0 otherwise. $\Delta Exit^i$ is the number of lane changes required to get from lane i to the exit lane.

5.2.2 The Gap Acceptance Model

The gap acceptance behavior is conditioned on the driver targeting either the right lane or the left lane. In these cases, the driver is assumed to evaluate the available adjacent gap in the target lane and decide whether to change lanes immediately or not. In order for the gap to be acceptable both the lead and lag gaps, shown in Figure 5.4, must be acceptable.

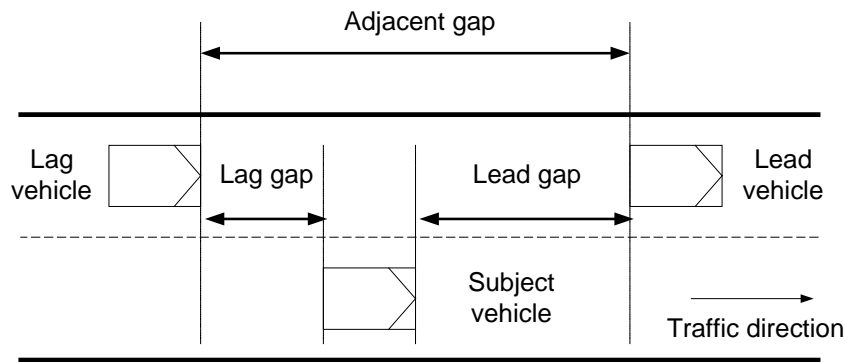


Figure 5.4 - The adjacent gap, subject, lead and lag vehicles and the lead and lag gaps

The lead critical gap decreases with the relative lead speed, i.e. it is larger when the subject vehicle is faster relative to the lead vehicle. The effect of the relative speed is strongest when the lead vehicle is faster than the subject. In this case, the lead critical gap quickly diminishes as a function of the speed difference. This result suggests that drivers perceive very little risk from the lead vehicle when it is getting away from them.

In gap acceptance model, the lag critical gap increases with the relative lag speed: the faster the lag vehicle is relative to the subject, the larger the lag critical gap is. In contrast to the lead critical gap, the lag gap does not diminish when the subject is faster. A possible explanation is that drivers may maintain a minimum critical lag gap as a safety buffer since their perception of the lag gap is not as reliable as it is for the lead gap due to the use of mirrors.

Median lead and lag critical gaps, as a function of the relative speeds are presented in Figure 5.5.

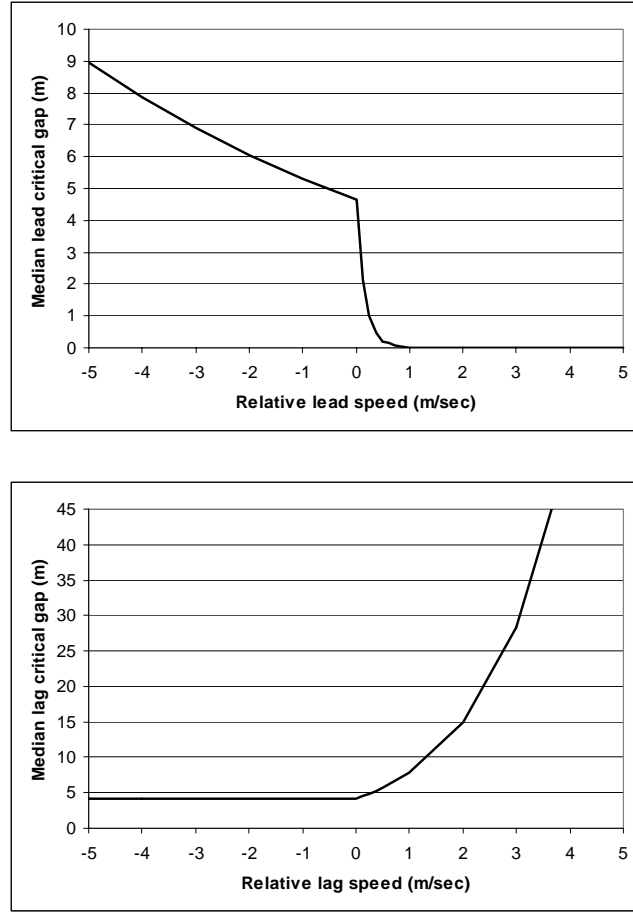


Figure 5.5 - Median lead and lag critical gaps as a function of relative speed

Estimated coefficients of the unobserved driver characteristics variable, ν_n , are negative for both lead and lag critical gaps. Hence, consistent with the interpretation of ν_n as negatively correlated with aggressive drivers, who require smaller gaps for lane-changing compared to timid drivers.

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

$$G_n^{lead,TL,cr}(t) = \exp \left(\begin{array}{l} 1.541 - 6.210 \text{Max}(0, \Delta V_n^{lead,TL}(t)) - \\ -0.130 \text{Min}(0, \Delta V_n^{lead,TL}(t)) - 0.008 \nu_n + \varepsilon_n^{lead}(t) \end{array} \right) \quad (5.8)$$

$$G_n^{lag,TL,cr}(t) = \exp \left(1.426 + 0.640 \text{Max}(0, \Delta V_n^{lag,TL}(t)) - 0.240 \nu_n + \varepsilon_n^{lag}(t) \right) \quad (5.9)$$

$$\varepsilon_n^{lead}(t) \sim N(0, 0.854^2) \text{ and } \varepsilon_n^{lag}(t) \sim N(0, 0.954^2)$$

5.2.3 Statistical test for model selection

The lane-changing model with explicit target lane choice extends the model with a myopic lane shift proposed by Toledo et al (2003). However, the myopic model cannot be viewed as nested within the model with explicit target lane choice, and therefore classic statistical tests cannot be applied to select between the two. Instead, we calculated three statistics that are often used for model selection (see Gouriéroux and Monfort 1995 for details): $\bar{\rho}^2$, the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC). These statistics, presented in Table 5.2, account for the larger number of parameters in the model with explicit target lane. With all these statistics, the model with explicit target lane choice has larger values, which indicates that it better fits the data, and therefore should be selected for prediction.

Table 5.2 - Statistics for the model with explicit target lane and the lane shift model

	Target Lane (U)	Change Direction (R)
Likelihood Value	-875.81	-888.78
$\bar{\rho}^2$	0.368	0.362
Number of Parameters (k)	31	26
Akaike information criteria (AIC)	-905.69	-914.78
Bayesian information criteria (BIC)	-940.82	-943.30

5.3 Summary

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

Estimation results for the target lane model indicate that the target lane choice is affected by lane-specific attributes, such as average speed and density, variables that relate to the path plan and the vehicle's interactions with other vehicles surrounding it. Gap acceptance decisions are affected by the relative subject speed with respect to the lead and lag vehicles.

It may be noted that the previous models only consisted of relative evaluation of current and adjacent lanes and did not include the lane-specific attributes. In contrast, the target lane model includes all lanes in the choice set and includes variables that capture the lane position and attributes. The estimation results indicate that the sign of these additional variables in the utility function are logical and match the intuitive expectations.

The inclusion of the additional variables also result a significant improvement in the model fit. This was confirmed by statistical tests using the estimation results of the explicit target lane choice model and a myopic lane shift model.

Chapter 6

Calibration and Validation

In this chapter, the target lane model is evaluated within the framework of a microscopic traffic simulation tool MITSIMLab. The evaluation is based on the comparison of the outputs of the target-lane model with that of the integrated lane-changing or lane shift model proposed by Toledo et al (2003). Both the models are calibrated and validated with sensor data from a section of I-80 using the calibration and validation framework described in Section 4.1.

The first section gives an overview of MITSIMLab. The methodology of calibrating the simulator is presented next, followed by the calibration results. The measures used for validation and the comparison results with the lane shift model are presented in the end.

6.1 MITSIMLab

MITSIMLab (Yang et al 2000) is a simulation-based laboratory that was developed for evaluating alternative traffic management system designs at the operational level and assisting in subsequent refinement. MITSIM, which represents the “real-world” with detailed traffic and network elements and mimics the behavior of individual drivers, provides as an ideal tool for testing the performance of different driving behavior models.

The various components of MITSIMLab are organized in three modules:

1. Microscopic Traffic Simulator (MITSIM)
2. Traffic Management Simulator (TMS)
3. Graphical User Interface (GUI)

The main elements of MITSIM are network components, travel demand and route choice and driving behavior. The road network is represented with nodes, links, segments and lanes. The vehicle movements and the traffic control and surveillance devices are represented at the microscopic level. Travel demand is simulated based on time-dependent origin-destination (OD) trip tables given as an input to the model. A probabilistic route choice model is used to capture drivers' route choice decisions, which may be based on historical or real-time travel time information.

The OD flows are translated into individual vehicles wishing to enter the network at a specific time. Each vehicle/driver combination is assigned behavior parameters (e.g. desired speed and aggressiveness) and vehicle characteristics. The vehicles move through the network according to acceleration and lane-changing models. The acceleration model captures drivers' response to conditions ahead as a function of relative speed, headway, and other traffic measures. The lane-changing model distinguishes between mandatory and discretionary lane changes. Merging, drivers' responses to traffic signals, speed limits, incidents, and tollbooths are also incorporated. The driving behavior models implemented in MITSIMLab were estimated and validated by Ahmed (1999) and Toledo (2003).

TMS mimics the traffic control system in the network under consideration. A wide range of traffic control and route guidance systems can be simulated. These include intersection controls, ramp control, freeway mainline control, lane control signs, variable speed limit signs, portal signals, variable message signs, and in-vehicle route guidance. TMS can represent different designs of such systems with logic at varying levels of sophistication (pre-timed, actuated, or adaptive). An extensive graphical user interface is used for both debugging purposes and demonstration of traffic impacts through vehicle animation. A detailed description of MITSIMLab appears in Yang and Koutsopoulos (1996) and Yang et al (2000).

The proposed target lane model has been implemented in MITSIM for the validation study. The acceleration model proposed by Ahmed (1999) has been used to simulate the longitudinal movement.

6.2 Aggregate Calibration

As detailed in Section 4.1, the calibration process involves adjusting the values of parameters of the behavioral models and estimating travel demand (in the form of OD flows) on the network being studied to obtain a better fit of the model output with the actual traffic flow. In this study, the lane-specific traffic sensor counts and speed data from I-80 network, described in Section 4.4 and shown again in Figure 6.1, have been used for calibrating both the target lane model and the lane shift model.

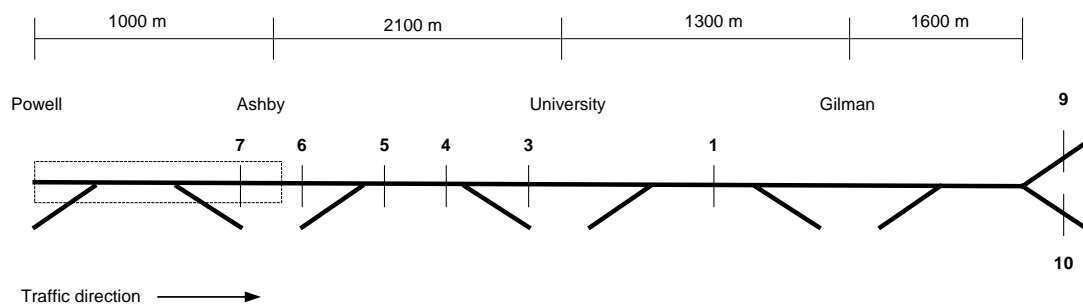


Figure 6.1 - The I-80 Network

The behavior models within MITSIMLab can be classified in two groups: driving behavior models and travel behavior models. Driving behavior includes acceleration, lane-changing, and intersection behavior models. Travel behavior is represented by the route choice model. Since, the chosen portion of I-80 is a corridor, route choice is not present in this application and the calibration is limited to driving behavior parameters.

The number of behavior parameters in the simulation model is very large. It is not feasible to calibrate all of them. Therefore a few parameters those have the most significant effect on the simulation results have been selected. The calibration focused on these parameters, while fixing the others to their previously estimated values.

The significant parameters identified in this study are as follows:

- Car-following parameters: acceleration and deceleration constants
- Free-flow parameters: desired speed distribution
- Lane-changing parameters: rightmost lane constant, current lane constant and HOV dummy*

* Only applicable for target lane model

The details of the lane-changing parameters of the explicit target lane model and the lane shift model have already been discussed in Section 2.2.1 and Section 5.2 respectively. The detailed description of the car-following parameters and the free-flow parameters is included in Appendix A.

In addition, MITSIMLab requires an origin to destination (OD) flow matrix as a necessary input representing travel demand. Since direct measurements of OD flows are not available, OD flows have also been estimated using the aggregate sensor data.

The same lane-specific sensor data is used both to calibrate behavior parameters and to estimate OD flows. The impact of each set of parameters on the simulation results cannot be isolated, and therefore they need to be calibrated jointly.

6.2.1 Problem Formulation

Aggregate calibration can be formulated as an optimization problem, which seeks to minimize a function of the deviation of the simulated traffic measurements from the observed measurements and of the deviation of calibrated values from the a-priori estimates of the OD flows (and potentially behavior parameter). The formulation presented here assumes that the observations are drawn during a period in which steady state traffic conditions prevail. That is, while OD flows and model parameters may vary for various observation days, these differences are due to random effects and do not represent a change in the underlying distributions of these variables. Furthermore, driving behavior parameters are assumed stable over the period of observation. It is important to note that the steady state assumption concerns the variability between observation days, and not within each observation day.

The formulation is shown below. The first and second terms in the objective function are a measure of deviation between observed and simulated measurements and between a priori OD flows and estimated OD flows respectively. The first constraint shows the dependence of simulated measurements on the driving behavior parameters, OD flows and the network conditions. The second constraint is nothing but the non-negativity constraint for the OD flows.

$$\begin{aligned}
& \min_{\beta, OD} \sum_{i=1}^N (M^{sim} - M_i^{obs})^T W^{-1} (M^{sim} - M_i^{obs}) + (OD - OD^o)^T V^{-1} (OD - OD^o) \\
& s.t. \quad M^{sim} = S(\beta, OD) \\
& \quad \quad OD \geq 0
\end{aligned} \tag{6.1}$$

Where, β is the vector of driving behavior parameters chosen for calibration, OD refers to the simulated OD flows, OD^o are the a priori OD flows, N is the number of days for which sensor data is available (five in this case), M^{sim} are the simulated measurements, M_i^{obs} are the observed measurements for day i , S is the simulation model function, which generates simulated traffic measurements, W is the variance-covariance matrix of the sensor measurements and V is the variance-covariance matrix of the OD flows.

Both traffic flows and speed measurements at all lane-specific sensor stations, from 14:30 to 18:00 for the first five out of total ten days have been used for the calibration. An iterative solution approach has been adapted, which is based on decomposition of the problem by parameter group (i.e. OD flows and driving behavior parameters). The proposed solution approach is shown in Figure 6.2.

Each iteration consists of several steps. At each step a set of parameters is calibrated, while the remaining parameters are fixed to their previous values. The OD estimation requires the generation of an assignment matrix, which itself is generated from the simulation model. Using this assignment matrix, OD estimation is performed. The new OD flows are then used to re-calibrate driving behavior parameters. The iterations are repeated until convergence is reached.

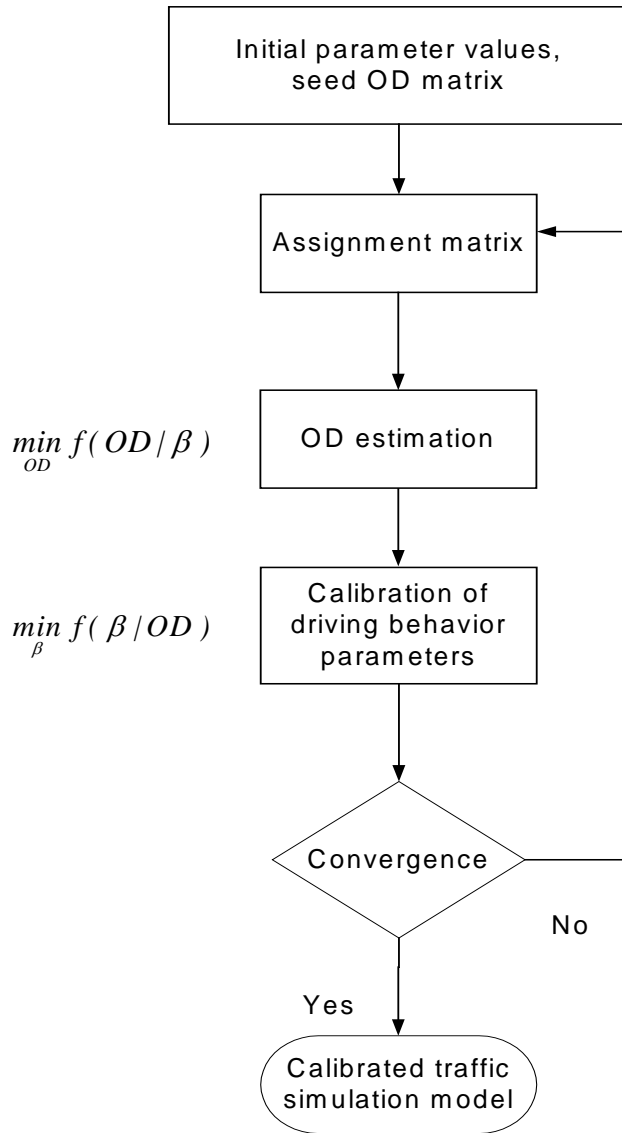


Figure 6.2 - Solution approach for the aggregate calibration problem

The OD estimation can be defined as the sub-problem of finding the OD flows, which are the most likely to have generated the observed traffic counts given the values of behavior parameter. The OD estimation problem requires three sets of inputs: traffic count measurements, a seed OD matrix (which includes a-priori estimates of OD flows) and an assignment matrix. The assignment matrix is estimated from the simulation model itself. Assuming a known assignment matrix A , link counts and a seed OD matrix the

problem is formulated as a constrained optimization problem (Cascetta and Nguyen 1988) given by:

$$\min_{X \geq 0} \sum_{i=1}^N (AX - Y_i^{obs})^T W^{-1} (AX - Y_i^{obs}) + (X - OD^o)^T V^{-1} (X - OD^o) \quad (6.2)$$

Where, X is the OD flows to be estimated, A is the assignment matrix that maps OD flows to counts at sensor locations

Once the OD flows are estimated their values are fixed. The driving behavior calibration sub-problem is formulated as:

$$\min_{\beta} \sum_{i=1}^N (M^{sim} - M_i^{obs})^T W^{-1} (M^{sim} - M_i^{obs}) \quad (6.3)$$

$$s.t. \quad M^{sim} = S(\beta, OD)$$

The number of behavior parameters in the simulation model is very large. It is not feasible to calibrate all of them. In this study, parameters that are likely to have the most significant effect on the simulation results have been selected. The calibration focused on these parameters, while fixing the others to their previously estimated values.

6.2.2 Calibration Results

The parameters chosen for calibration and their initial and calibrated values are shown in Table 6.1:

Table 6.1 - Initial and calibrated values of the parameters of the target-lane model

Parameter		Initial Value	Calibrated Value
Car-Following	Acceleration Constant	0.040	0.042
	Deceleration Constant	-0.042	-0.084
Desired Speed	Mean	0.100	0.175
	Variance	0.150	0.254
Lane-changing	Rightmost Lane Constant	-1.696	-1.052
	Current Lane Dummy	2.686	2.800
	HOV Dummy	0.000	1.521

The overall fit of the calibrated simulated traffic counts and speeds to the observed values has been evaluated using two goodness of fit statistics Root Mean Square Error and Root Mean Square Percent Error.

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (M_n^{sim} - M_n^{obs})^2} \quad (6.4)$$

$$RMSPE = \sqrt{\frac{1}{N} \sum_{n=1}^N \left(\frac{M_n^{sim} - M_n^{obs}}{M_n^{obs}} \right)^2} \quad (6.5)$$

Where, M_n^{obs} and M_n^{sim} are the observed and simulated measurements at space-time point n , respectively.

The results are presented in Figure 6.3 and summarized in Table 6.2.

Table 6.2 - Fit of the calibrated model to the observed traffic measurements

Statistic	Count (Veh/15 Minutes)	Speed (m/sec)
RMSE	26.1	3.23
RMPSE (%)	9.5	10.3

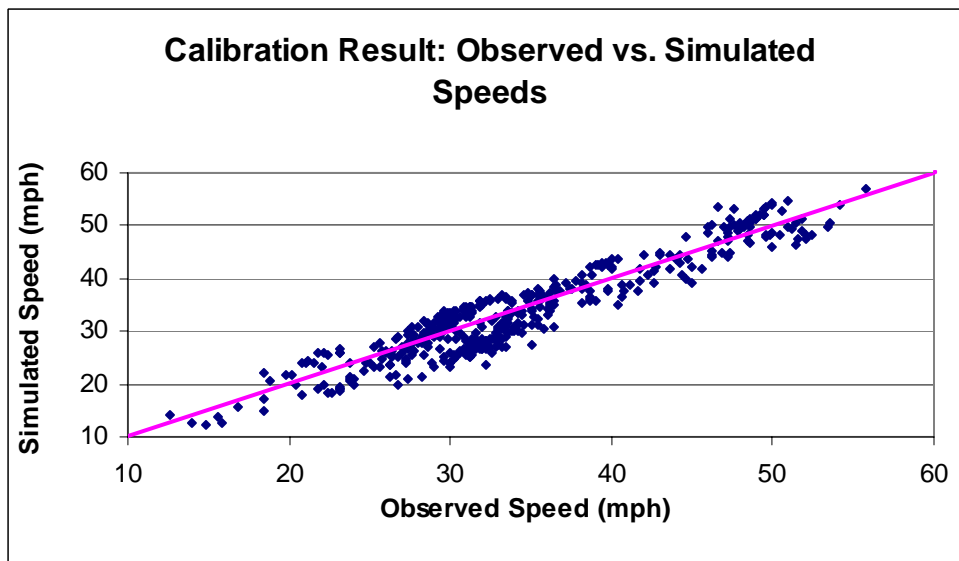
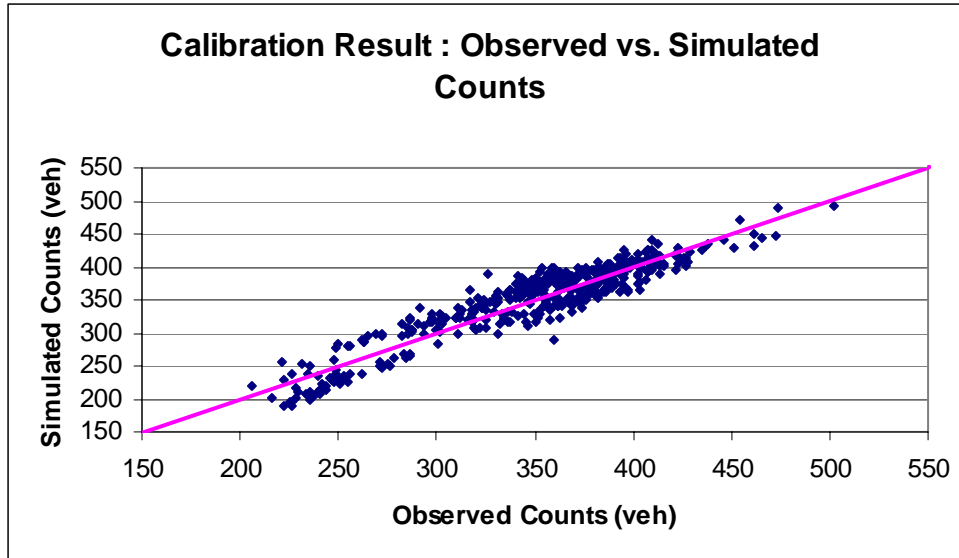


Figure 6.3 - Calibration results for the target-lane model

6.3 Aggregate Validation

The purpose of aggregate validation is to determine the extent to which the simulation model replicates the real system. At this step, the behavior parameters obtained in the aggregate calibration step are fixed and the model predictions are compared against the second set of traffic measurements, which have not been used for calibration. A separate OD is estimated for the validation measurements.

The model validation is comparative. In this case, the performance of the target-lane model is compared with the performance of the model with myopic lane shift model proposed by Toledo et al (2003). Both models are implemented in MITSIMLab. The two versions are calibrated using the available lane specific sensor data. Different measures of performance derived from the aggregate sensor and trajectory data (listed in the next section) are used in the validation process.

6.3.1 Measures of performance

The validity of the calibrated model is verified with the help of some statistics calculated from the actual observations and outputs of simulation systems. These measures of performance (MOPs) are selected based on their relevance to the evaluation of the lane-changing model. The MOPs that have been identified for validation in this case are:

- Lane-specific sensor speeds
- End lane distribution of vehicles with respect to the starting lane
- Average lane changes by starting lane
- Number of lane changes by vehicles
- Lane changes From and To lanes

It is assumed that these statistics capture the effect of the lane-changing model, and that if the simulation is able to replicate these field observations well, this is an indication that the lane-changing model is valid. For the lane-specific speed, the sensor data collected from 14:30 to 18:00 over the sixth to tenth day have been used for the validation. For the other measures of performances, aggregate trajectory data collected from 14:35 to 18:05 have been used. It may be noted that these data have not been used in calibration.

6.3.2 Simulation replications

Since the simulation model is stochastic in nature, MOPs need to be calculated from a number of independent replications. The number of replications to be used has been obtained using a sequential procedure suggested by Fishman (1978). In this approach one replication at a time is run until a suitable stopping criterion is met. Assuming that the

outputs, Y_i , from different simulation runs are normally distributed, the following criterion may be used:

$$R \geq R_i = \max \left(2, \left(\frac{s_R(Y_i) t_{\alpha/2}}{d_i} \right)^2 \right) \quad (6.6)$$

Where, R is the number of replications performed, R_i is the minimum number of replications required to estimate the mean of Y_i with tolerance d_i , $s_R(Y_i)$ is the sample standard deviation of Y_i based on R replications and $t_{\alpha/2}$ is the critical value of the t-distribution at significance level α .

6.3.3. Goodness of fit measures

A number of goodness of fit measures has been used to evaluate the overall performance of a simulation model. These measures include the root mean square error ($RMSE$) and the root mean square percent error ($RMSPE$) that have been presented in the Section 6.2.2. $RMSE$ and $RMSPE$ penalize large errors at a higher rate relative to small errors. Other measures include:

- Mean error (ME)
- Mean percent error (MPE)
- Theil's Inequality Coefficient

ME and MPE indicate the existence of systematic under-prediction or over-prediction in the simulated measurements. These measures are given by:

$$ME = \frac{1}{N} \sum_{n=1}^N (Y_n^{sim} - Y_n^{obs}) \quad (6.7)$$

$$MPE = \frac{1}{N} \sum_{n=1}^N \frac{Y_n^{sim} - Y_n^{obs}}{Y_n^{obs}} \quad (6.8)$$

Where, Y_n^{obs} and Y_n^{sim} are the averages of observed and simulated measurements at space-time point n , respectively calculated from all available data (i.e. several days of observations and/or multiple simulation replications).

Another measure that provides information on the relative error is Theil's inequality coefficient, U :

$$U = \frac{\sqrt{\frac{1}{N} \sum_{n=1}^N (Y_n^{sim} - Y_n^{obs})^2}}{\sqrt{\frac{1}{N} \sum_{n=1}^N (Y_n^{sim})^2} + \sqrt{\frac{1}{N} \sum_{n=1}^N (Y_n^{obs})^2}} \quad (6.9)$$

U is bounded, $0 \leq U \leq 1$. $U = 0$ implies perfect fit between the observed and simulated measurements. $U = 1$ implies the worst possible fit. Theil's inequality coefficient may be decomposed to three proportions of inequality: the bias (U^M), variance (U^S) and covariance (U^C) proportions, which are, respectively, given by:

$$U^M = \frac{(\bar{Y}^{sim} - \bar{Y}^{obs})^2}{\frac{1}{N} \sum_{n=1}^N (Y_n^{sim} - Y_n^{obs})^2} \quad (6.10)$$

$$U^S = \frac{(s^{sim} - s^{obs})^2}{\frac{1}{N} \sum_{n=1}^N (Y_n^{sim} - Y_n^{obs})^2} \quad (6.11)$$

$$U^C = \frac{2(1 - \rho) s^{sim} s^{obs}}{\frac{1}{N} \sum_{n=1}^N (Y_n^{sim} - Y_n^{obs})^2} \quad (6.12)$$

ρ is the correlation between the two sets of measurements.

6.3.4 Validation Results

Lane-specific Speeds

A separate set of lane-specific speed measurements from sensors (not used for calibration) has been used for validation purpose. The comparisons of the goodness of fit measures are presented in Table 6.3 and Figure 6.4.

Table 6.3 - Goodness of fit statistics for the traffic speed comparison

Statistic	Target Lane Model	Lane shift Model	% Improvement
Root Mean Square Error, m/sec	3.10	3.92	20.76
Root Mean Square Percent Error (%)	12.15	14.89	18.39
Mean Error (m/sec)	-0.83	1.59	47.83
Mean Percent Error (%)	-3.33	5.17	35.68
U (Theil's inequality coefficient)	0.051	0.063	19.78
U_m (bias proportion)	0.071	0.165	56.97
U_s (variance proportion)	0.007	0.016	56.25

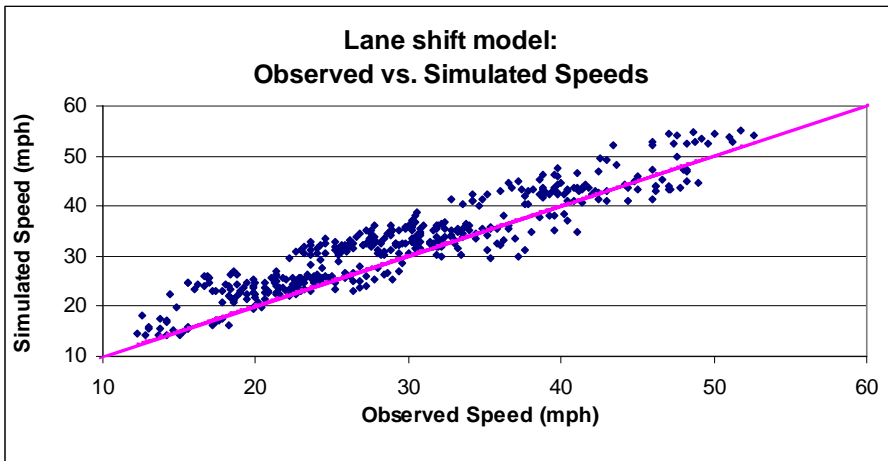
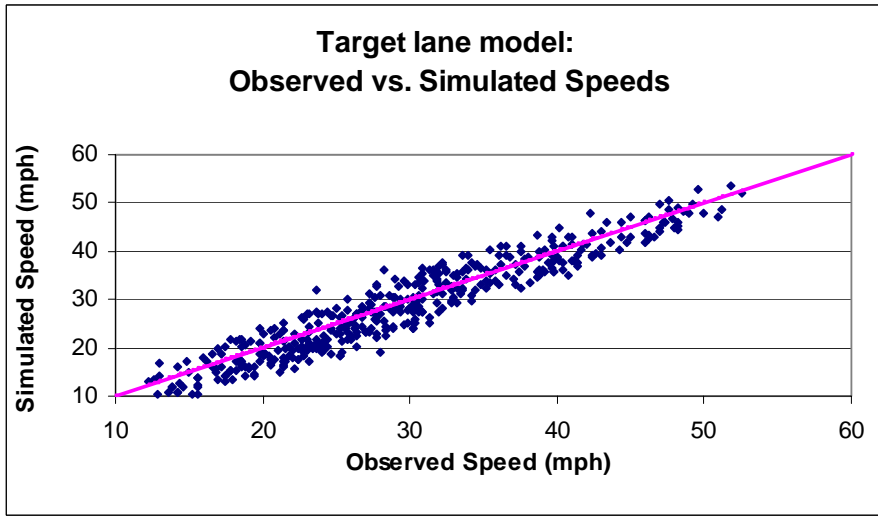


Figure 6.4 - Comparison of lane-specific speeds

As with the results in the previous sections, the target lane model consistently performs better particularly in terms of Mean Error and Mean Percent Error. Graphs showing the results of the comparison between the lane-specific speeds observed in the sensor data and in the simulation output for each lane in each sensor station using the explicit target lane model and the lane shift model are shown in Appendix B. In case of the lane shift model, considerable discrepancy in the traffic speeds is observed. The discrepancy in the lane distribution can be a potential source of the speed mismatch in the lane shift model since the erroneously lower calculations of the flows in the HOV lane result in increased speed outputs of the HOV lanes and reduced speed outputs in the other lanes.

End Lane Distribution

The distribution of vehicles across lanes at the end of the section with respect to the starting lane has been extracted from the aggregate trajectory data and compared with the simulated lane distributions of both the models. Figure 6.5 present the results of the comparison. The values of the goodness of fit statistics that were calculated for this MOE are shown in Table 6.4.

Table 6.4 - Overall Goodness of fit Statistics for the Lane Distribution Data

Statistic	Lane Shift Model	Target Lane Model	% Improvement
RMSE (fraction)	0.041	0.032	20.04
U (Theil's inequality coefficient)	0.076	0.061	20.76

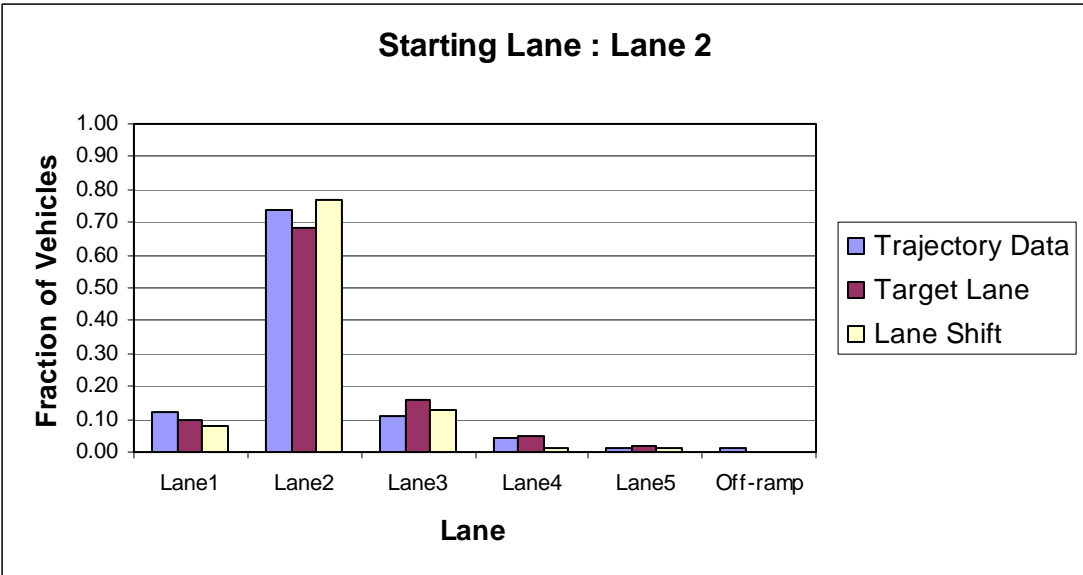
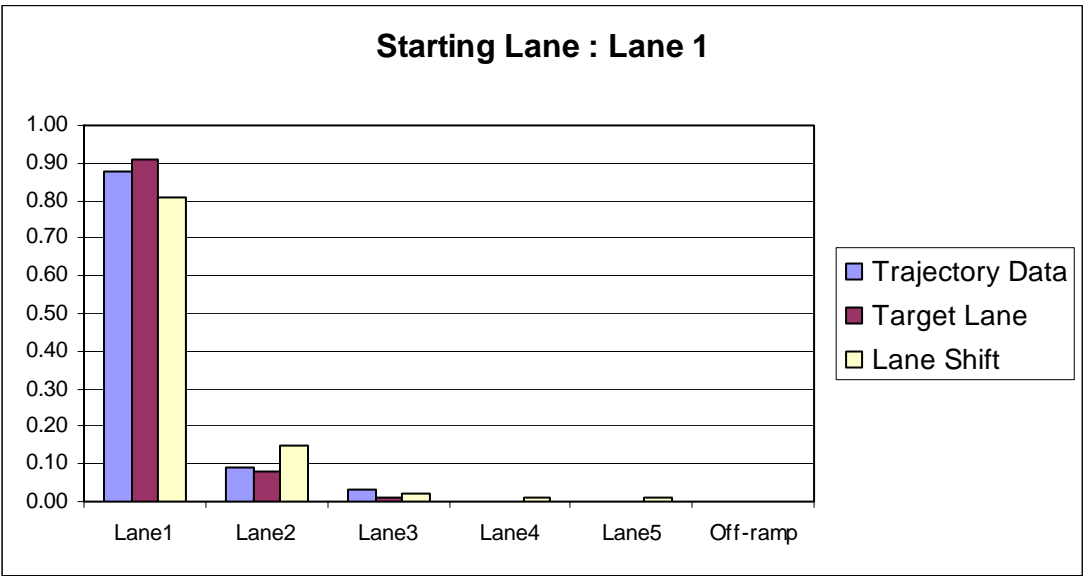


Figure 6.5 (A) - End lane distribution of vehicles observed in the trajectory data and in the simulation output

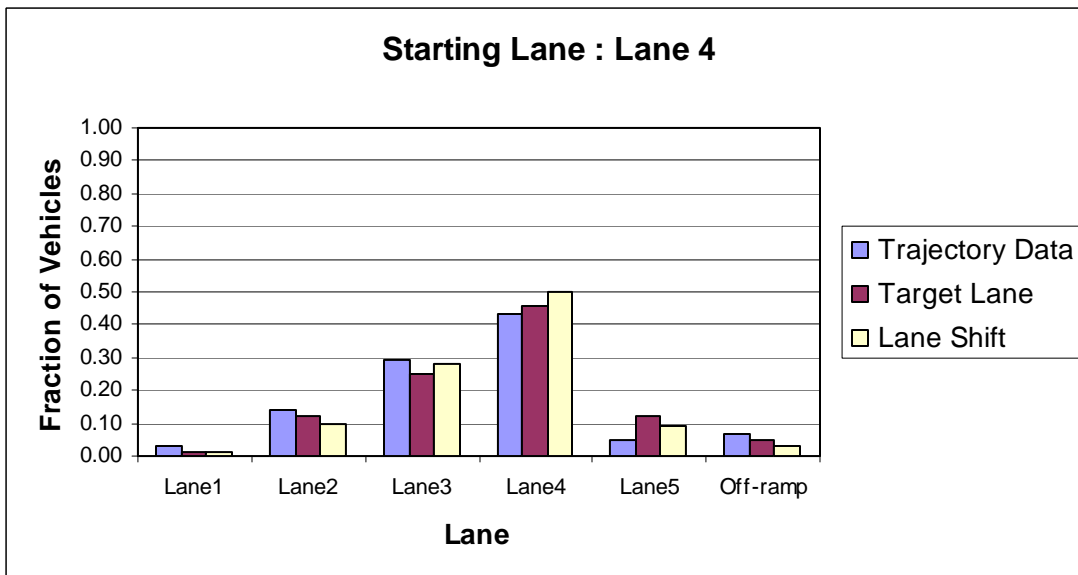
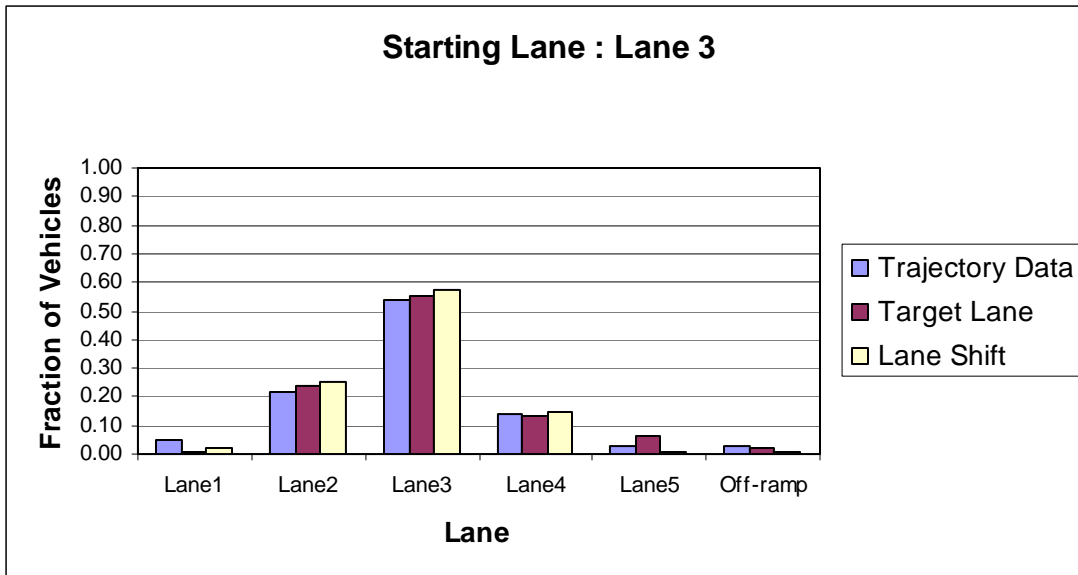


Figure 6.5 (B) - End lane distribution of vehicles observed in the trajectory data and in the simulation output

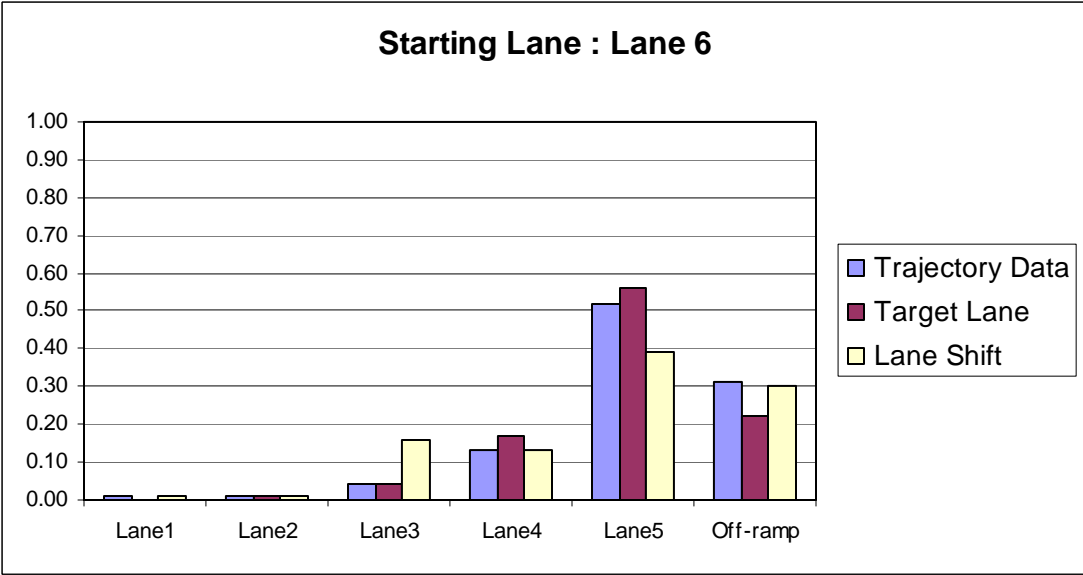
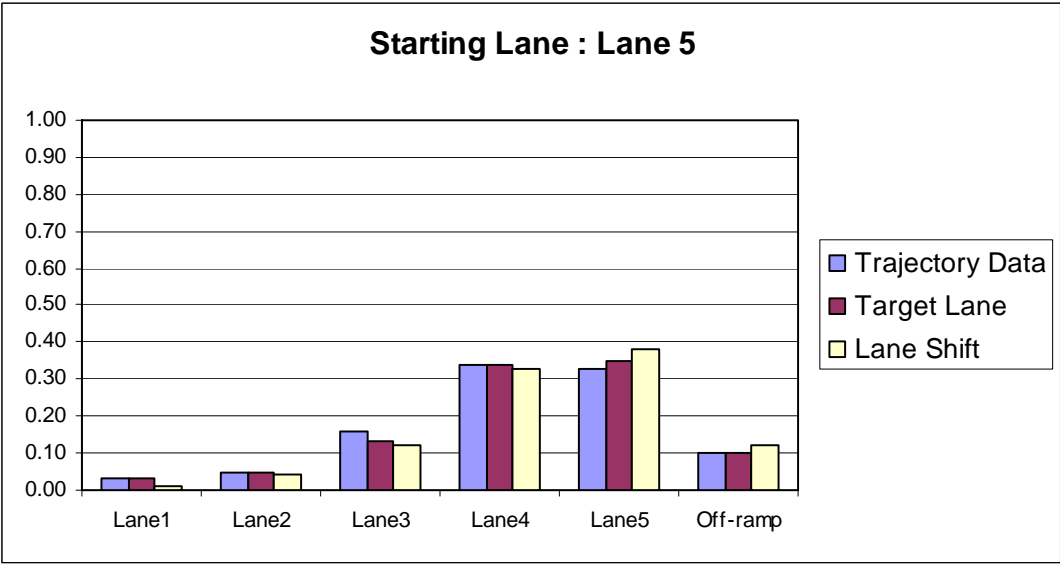


Figure 6.5 (C) - End lane distribution of vehicles observed in the trajectory data and in the simulation output

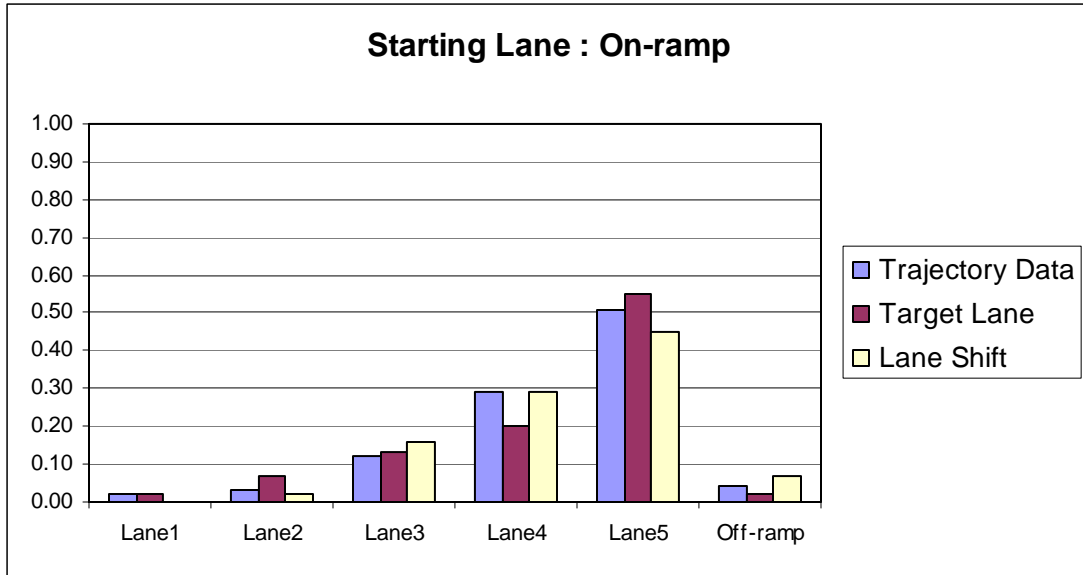


Figure 6.5 (D) - End lane distribution of vehicles observed in the trajectory data and in the simulation output

Overall, the model with explicit target lane matched the observations better and as observed in Table 6.4, the RMSE is 0.032 for the target lane model and 0.041 for the lane shift model. A closer look at the results of the lane shift model shows, a significant proportion of the error is due to incorrect representation of the HOV lane (Table 6.5). The RMSE of the percentage of vehicles moving to the HOV from all starting lanes is 4.8% for the lane shift model and 2.1 % for the target lane model. This result indicates that the lane shift lane-changing model is unable to correctly capture the attractiveness of the HOV lanes and therefore underestimated its use. These underestimations of the HOV flows is a potential source of discrepancy in the lane-specific traffic speed outputs, since the reduced flow rates on the HOV lanes result in reduced speeds on these lanes.

Table 6.5 - Goodness of fit statistics for the lane distribution data for the HOV lane

Statistic	Lane Shift Model	Target Lane Model	% Improvement
RMSE (fraction)	0.051	0.031	66.09
U (Theil's inequality coefficient)	0.073	0.043	65.84

Average Lane changes by Starting Lane

The average lane changes with respect to the starting lane by the two model outputs were compared against the aggregate trajectory observations. The results are summarized in Table 6.6 and Figure 6.6.

Table 6.6 - Average lane changes by starting lane

Time	Starting Lane							Powell On	Avg. by period
	1	2	3	4	5	6			
Trajectory Data	0.21	0.41	0.85	1.02	1.20	0.79		1.70	0.79
Lane Shift Model	0.28	0.34	0.83	0.93	0.99	0.82		1.43	0.73
Target Lane Model	0.17	0.38	0.75	1.10	1.25	0.90		1.83	0.81

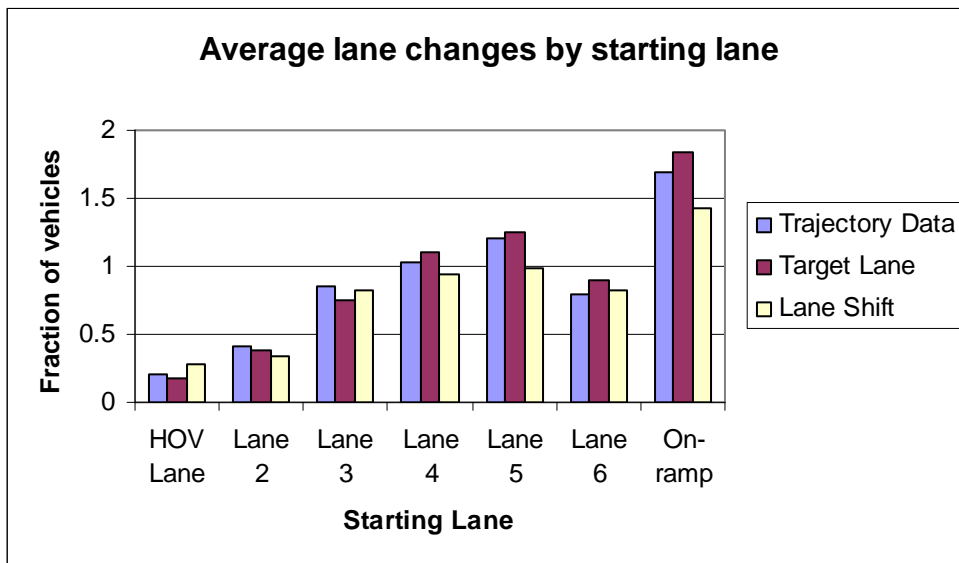


Figure 6.6 - Average lane changes by starting lane

In general the lane shift model underestimated the number of lane changes and the target lane model overestimated it. According to the trajectory data, on an average each vehicle made 0.79 lane changes within the observation period. The average lane changes predicted by the target lane model was 0.81 and the lane shift model was 0.73. The goodness of fit measures is presented in Table 6.7.

Table 6.7 - Goodness of fit Statistics for the Average Lane Changes by Starting Lane

Statistic	Lane Shift Model	Target Lane Model	% Improvement
RMSE (fraction)	0.141	0.090	38.44
U (Theil's inequality coefficient)	0.074	0.042	43.48

Lane changes by Vehicles

The number of lane-changes by vehicles as observed in the trajectory data has been compared against the simulated results of the target lane model and the lane shift model. The results are presented in Figure 6.7. It was observed that the lane shift model under predicted the number of more-than-one lane changes. This is probably due to the fact that in the lane shift model only adjacent lanes are in the choice set of the driver and the higher level of service prevailing in lanes further away are not taken into account. The target lane model performed much better than the lane shift model particularly in terms of predicting the higher number of lane changes. The goodness of fit statistics is presented in Table 6.8. RMSE for the fraction of vehicles in the lane shift model and the target lane model were 0.040 and 0.024 respectively indicating an improvement of 38.33 %.

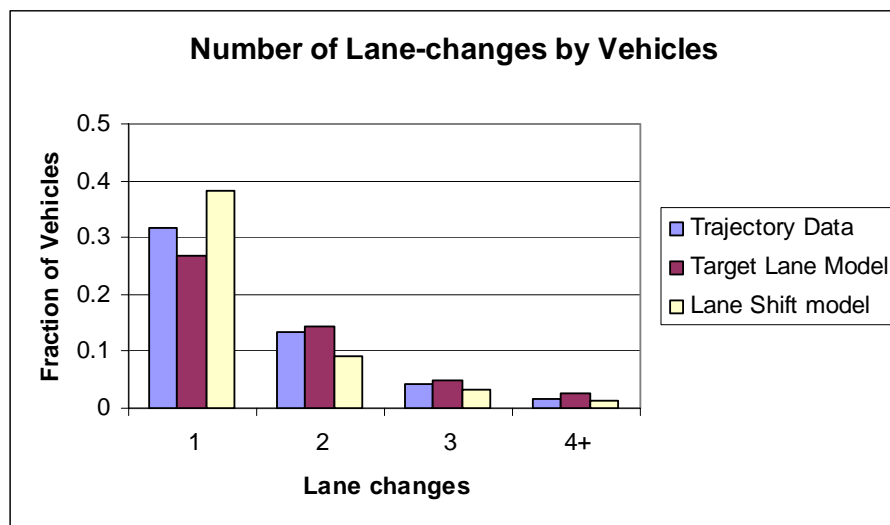


Figure 6.7 - Number of lane changes by vehicles observed in the trajectory data and in the simulation output

Table 6.8 - Goodness of fit Statistics for the Average Lane Changes by Vehicle

Statistic	Lane Shift Model	Target Lane Model	% Improvement
RMSE (fraction)	0.040	0.024	38.33
U (Theil's inequality coefficient)	0.074	0.046	37.18

Lane changes From and To lane

The number of lane changes by From (starting) and To (ending) lanes was also compared. As seen in Figure 6.8, the lane shift model has a significantly small number of lane-changes to the HOV Lane. The target lane model performs much better in this respect. The goodness of fit is compared in Table 6.9.

Table 6.9 - Goodness of fit Statistics for the Lane Changes From and To Lane

Statistic	Lane Shift Model	Target Lane Model	% Improvement
RMSE (fraction)	0.021	0.012	42.9
U (Theil's inequality coefficient)	0.055	0.033	41.1

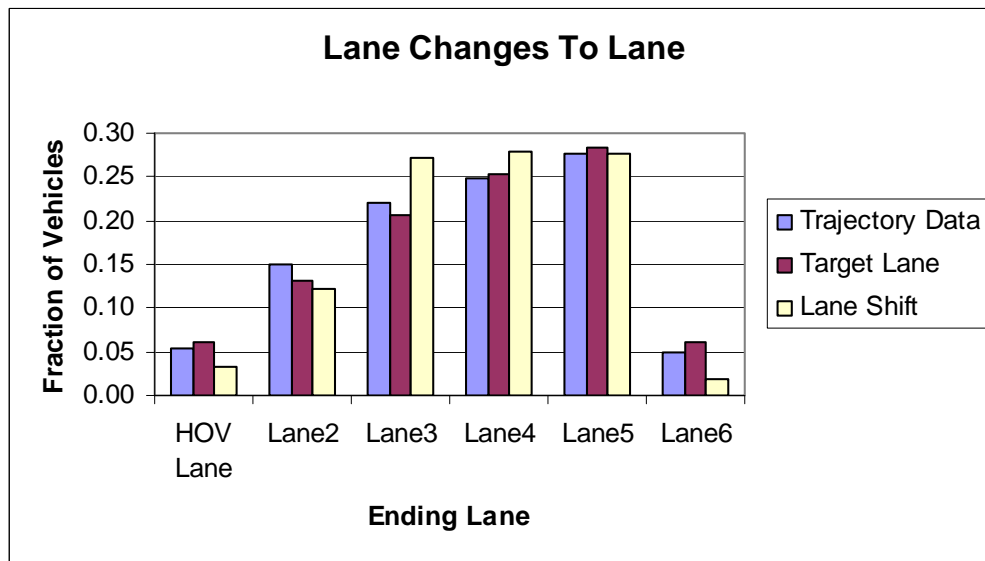
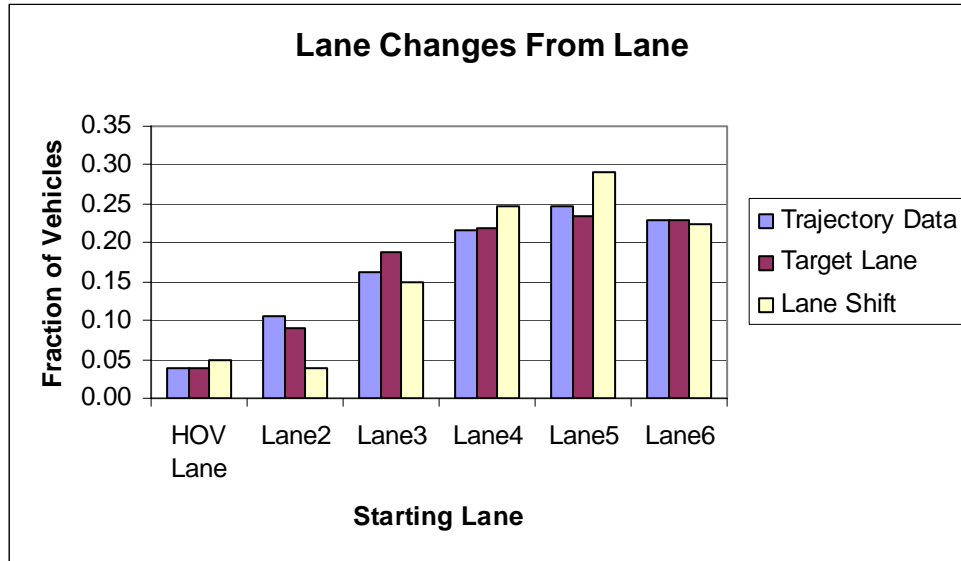


Figure 6.8 - Lane changes From and To lanes

6.4 Summary

The target lane model has been implemented in a microscopic traffic simulator MITSIMLab and tested with data from a section of I-80, CA network. The performance of the model has been compared with that of the lane shift model (Toledo 2003). Both models have been calibrated with the aggregate sensor counts and speeds from the collection site. A different set of aggregate speeds, along with aggregate trajectory data collected from the site, have been used for validation purpose. The two model

performances have been compared in terms of lane-specific speeds, end lane-distribution of vehicles with respect to starting the lane, lane changes To and From lanes and number of lane changes by vehicles. The target lane model outputs have a closer match with the field observations in terms of all the criteria. Particularly, the target-lane model performed much better compared to the lane shift model in predicting the number of lane changes to the HOV lane and the fraction of vehicles using the HOV lane. Therefore it can be concluded that the impact of exclusive lanes on drivers' lane selection has been better captured in the explicit target lane model.

Chapter 7

Conclusions

This chapter summarizes the research reported in this thesis and highlights the major contributions. Directions for future research are suggested in the end.

7.1 Summary

A new lane-changing model with explicit choice of a target lane is presented to capture the lane-changing behavior in presence of exclusive lanes. This approach differs from existing models that assume that drivers evaluate the current and adjacent lanes and choose a direction of change (or not to change) based on the relative utilities of these lanes. While the proposed model is most useful in presence of exclusive lanes and similar cases where there exists a high difference in the level of service among the lanes, it is applicable to any freeway situation. The model structure can also capture drivers' preference to specific lanes, such as in the case when travel lanes and passing lanes are defined.

The model consists of two choices: the selection of a target lane and gap acceptance. A random utility approach has been adopted to model both components. The model structure accounts for correlations among the choices made by the same driver over choice dimensions and time that are due to unobserved individual-specific characteristics by introducing a driver-specific random term. This driver-specific random term is included in all model components. Missing data due to the limitations of the data collection are also account for.

Parameters of all components of the model have been estimated jointly using a maximum likelihood estimator and detailed vehicle trajectory data. Estimation results show that the target lane choice is significantly affected by lane-specific attributes, such

as average speed and density as well as variables that relate to the path plan and the vehicle's interactions with other vehicles surrounding it. Gap acceptance is modeled by comparing the available space lead and lag gaps to the corresponding critical gaps. Critical gaps are found to depend on the relative subject speed with respect to the lead and lag vehicles.

Statistical tests using the estimation results showed that the lane-changing model with explicit target lane choice is superior to previous model with a myopic lane shift. This result is further strengthened by the validation case study, in which the results obtained from a microscopic traffic simulator that incorporated the new lane-changing model have been compared with the results using the lane shift model. The simulator has been applied to a multi-lane freeway section that includes an HOV lane. The model parameters have been calibrated before the validation exercise and the effect of the HOV lane has been captured during this aggregate calibration process by introducing an HOV dummy. The analysis of test statistics calculated in the aggregate validation stage indicate that the target lane model provides significantly better prediction in terms of all measures of performance: lane specific speed measurements, end lane distributions, lane changes To and From lanes and number of lane changes by vehicles.

7.2 Research Contributions

The objective of this research was to develop a lane-changing model that is applicable in situations with presence of unlimited access exclusive lanes, as well as normal freeway situations. This thesis contributes to state-of-the-art in lane-changing models in the following respects:

- A new lane-changing model with explicit choice of target lane is proposed. This model is based on the notion that the drivers make lane-changing decisions based on target lanes rather than relative evaluation of the current and the adjacent lanes. The target lane is the most desirable lane of the driver and immediate lane-changing actions are based on the selected target lane depending upon gap availability.
- Based on these concepts, a target lane model structure is developed. This model structure is flexible enough to accommodate lane-changing behavior in presence of

exclusive lanes. The generic structure of the model allows it to be used to specify models for different driving environments, such as freeways or urban streets, and is particularly suitable for situations when there exists a high differential in LOS among different lanes of the road. The model structure accounts for missing data and correlations among the choices made by the same driver over choice dimensions and time.

- The parameters of the target lane model are estimated using trajectory data. Estimation results show that lane-specific variables are significant in lane selection. A significant improvement in goodness of fit is observed over the lane shift model.

- The target lane model is calibrated for an unlimited access HOV lane situation. The value of the HOV dummy is determined during this calibration process using sensor data. The positive validation results strengthen the necessity of including the concept of the target lane in the lane-changing model.

7.3 Future Research

Detailed trajectory data from sites with exclusive lanes was not available during this research and the exclusive lane-specific characteristics were represented only in terms of the HOV dummy. It was not possible to estimate separately the effects of variables affecting the HOV lane selection with the available data. Further research with detailed trajectory data from sites with various exclusive lane configurations is required to develop more detailed lane-choice models for different exclusive lane situations.

The target lane model framework is also particularly suitable for application in other urban and freeway situations where there exists pronounced difference in LOS among different lanes. The model can be extended to capture localized lane-changing behaviors: the distinct passing behavior observed in several European countries for example. Comprehensive data containing detailed information about various lane-specific variables, collected from varying geometric and traffic characteristics, will enable the development of more robust models that will be more generally applicable to model urban freeways traffic.

The target lane choice of the driver is assumed to be instantaneous in this model. However, in reality, some drivers may have a short-term plan regarding lane changing. That is the driver may select a target lane and make various tactical choices over a stretch

of time to get to the target lane. For example, a driver opting to overtake the vehicle in his front may make take a tactical decision to move to the adjacent lane in spite of the current lane being his target lane. Future research should address such short term goal based lane changing phenomena.

Modeling the cooperative lane-changing behaviors (e.g. courtesy yielding) have not been included within the scope of this research. Future research should capture the effects of cooperation among driver, particularly in the merging areas near the on ramps.

The interaction between the lane-changing and acceleration behavior of the driver is also ignored in the current model whereas, in real world, drivers are likely to accelerate and decelerate based on their tactical short-term plan to reach their target lane. Hence, there is the need to develop more detailed driving behavior models based on the concept of generalized target lane capable of capturing interdependencies between lane-changing and acceleration behaviors.

Appendix A

Acceleration Models in MITSIM

The acceleration models implemented in MITSIM (Ahmed, 1999) are described in this section.

MITSIM considers two acceleration regimes: free-flow and car following. The free flow acceleration regime, in which the vehicle travels at his/her desired maximum speed, prevails when there is no lead vehicle or the lead vehicle in front is far enough ahead that it has no impact on the subject vehicle. The free-flow acceleration model has the following form:

$$a_n^{ff}(t) = \lambda^{ff} \times [X_n^{DS}(t - \tau_n) \beta^{DS} - V_n(t - \tau_n)] + \varepsilon_n^{ff}(t) \quad (\text{A.1})$$

Where, a_n^{ff} is the free flow acceleration of driver n at time t , λ^{ff} is the constant sensitivity, $X_n^{DS}(t - \tau_n)$ is the vector of explanatory variables affecting the desired speed, τ_n is the reaction time of the driver, β^{DS} is the corresponding coefficient, $[V_n(t - \tau_n)]$ is the current speed of the driver at time $(t - \tau_n)$, $\varepsilon_n^{ff}(t)$ is the random term associated with free flow acceleration.

The model was estimated to contain the following behavioral parameters:

$$a_n^{ff}(t) = \beta_{sens} \cdot [\alpha + \beta_{fvs} \cdot V_n^{front}(t - \tau_n) - \beta_{hv} \cdot \delta_n^{heavy} + \beta_d \cdot \delta[k_n(t - \tau_n)] - V_n(t - \tau_n)] + \varepsilon_n^{ff}(t) \quad (\text{A.2})$$

Where,

β_{sens} is the sensitivity constant, α is a constant, $V_n^{front}(t - \tau_n)$ is the front vehicle speed at time $(t - \tau_n)$, δ_n^{heavy} is the heavy vehicle dummy, $\delta[k_n(t - \tau_n)]$ is the indicator for density.

If the headway is less than the threshold, the car-following model dictates acceleration decisions when a lead vehicle is near enough to the subject vehicle that the subject must accelerate or decelerate to maintain a safe following distance. The car-following acceleration (when the relative speed is positive, deceleration when the relative speed is negative) is shown in Equation A.3.

$$a_n^{cf,g}(t) = s[X_n^{cf,g}(t - \xi\tau_n)]f[\Delta V_n(t - \tau_n)] + \varepsilon_n^{cf,g}(t) \quad (\text{A.3})$$

Where,

$s \left[X_n^{cf,g} (t - \xi \tau_n) \right]$ is sensitivity, a function of a vector of explanatory variables affecting the car following acceleration sensitivity at time $(t - \xi \tau_n)$, $f \left[\Delta V_n (t - \tau_n) \right]$ is the stimulus, a function of relative speed between front vehicle and subject vehicle at time $(t - \tau_n)$ and $\varepsilon_n^{cf} (t)$ is the random term associated with car following acceleration of driver n at time t .

The model was estimated to contain the following behavioral parameters:

$$\begin{aligned}
 a_n^{cf,acc} (t) &= \alpha \cdot \frac{V_n(t)^{\beta_s}}{\Delta X_n(t)^{\beta_h}} \cdot k_n(t)^{\beta_d} \left| \Delta V_n(t - \tau_n) \right|^{\beta_{rs}} + \varepsilon_n^{cf,acc} (t) \\
 a_n^{cf,dec} (t) &= \alpha \cdot \frac{1}{\Delta X_n(t)^{\beta_h}} \cdot k_n(t)^{\beta_d} \left| \Delta V_n(t - \tau_n) \right|^{\beta_{rs}} + \varepsilon_n^{cf,dec} (t)
 \end{aligned}
 \tag{A.4}$$

where,

α is a constant, $V_n(t)$ is the subject speed at time t , $\Delta X_n(t)$ is the space headway at time t , $k_n(t)$ is an indicator for density ahead of subject and $\Delta V_n(t - \tau_n)$ is the difference between the front vehicle speed and the subject speed.

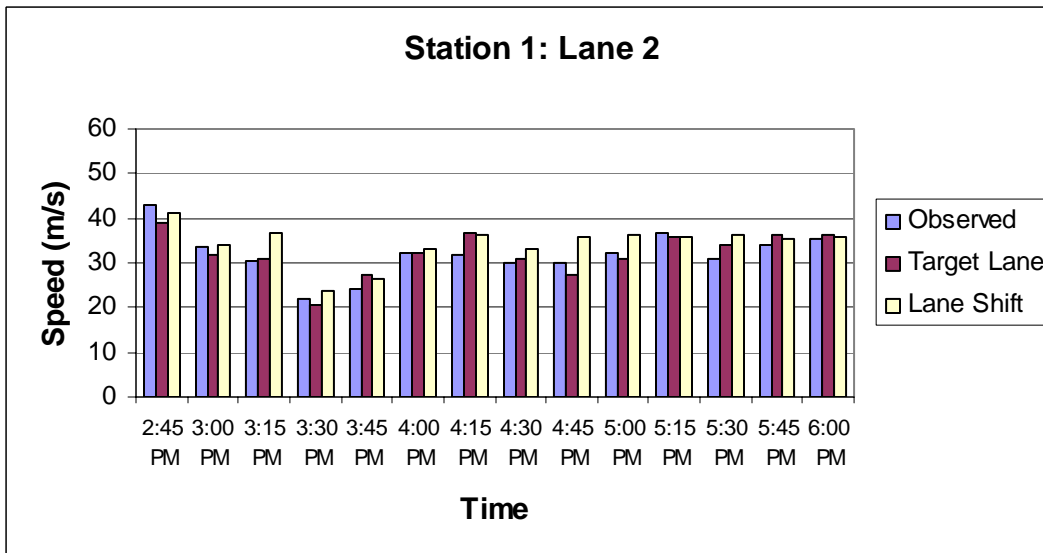
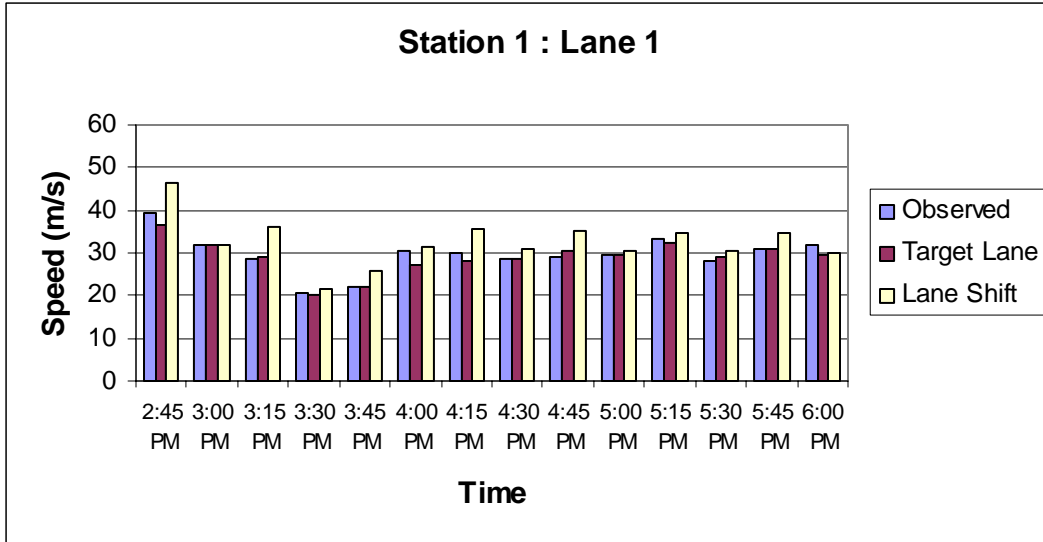
The estimation results of the model structure using the trajectory data from Arlington, VA (Toledo 2003) are presented in Table A.1.

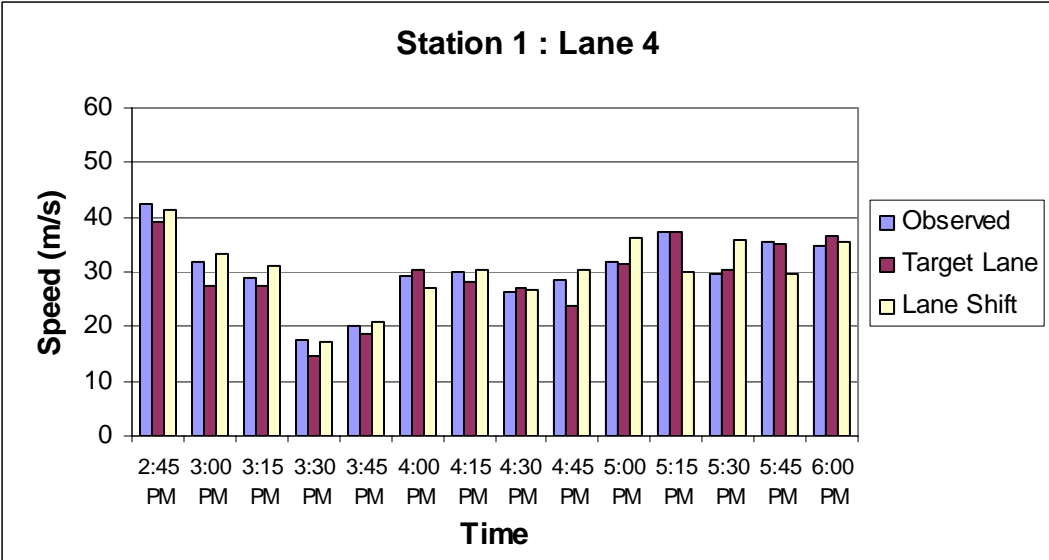
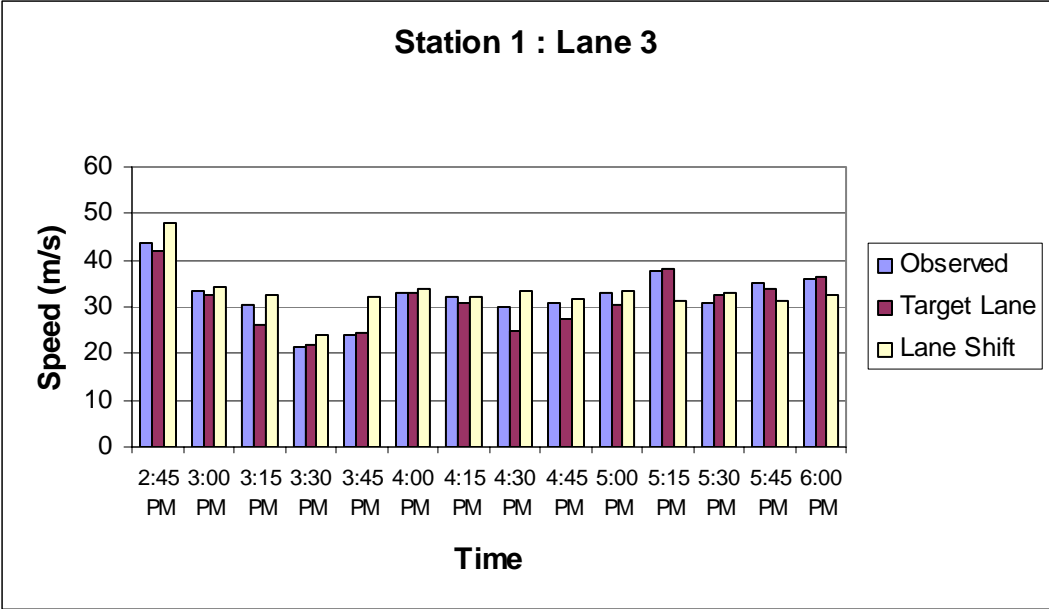
Table A.1 - Estimation results for the acceleration model

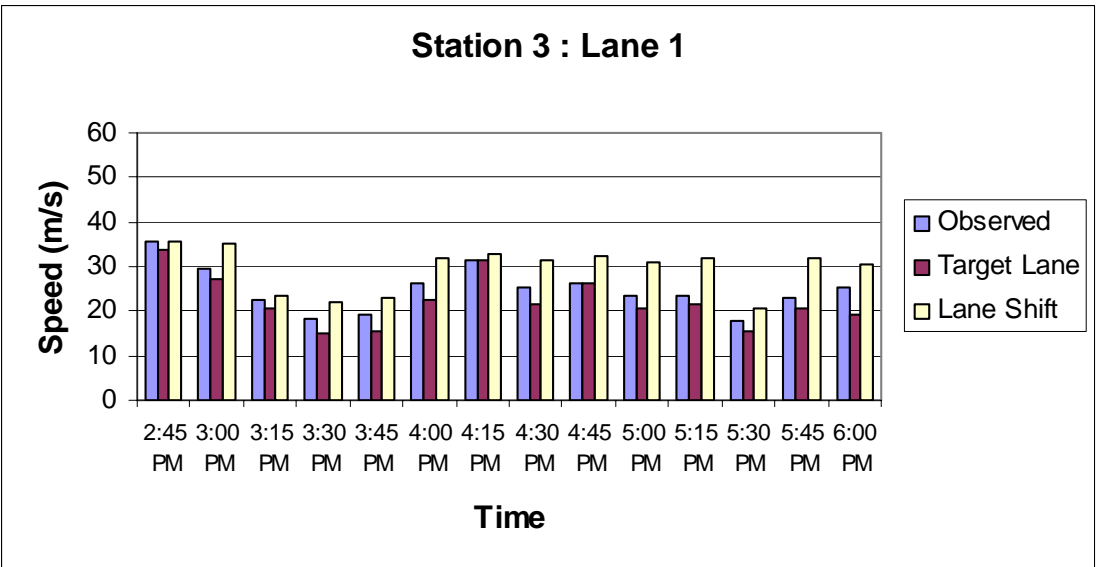
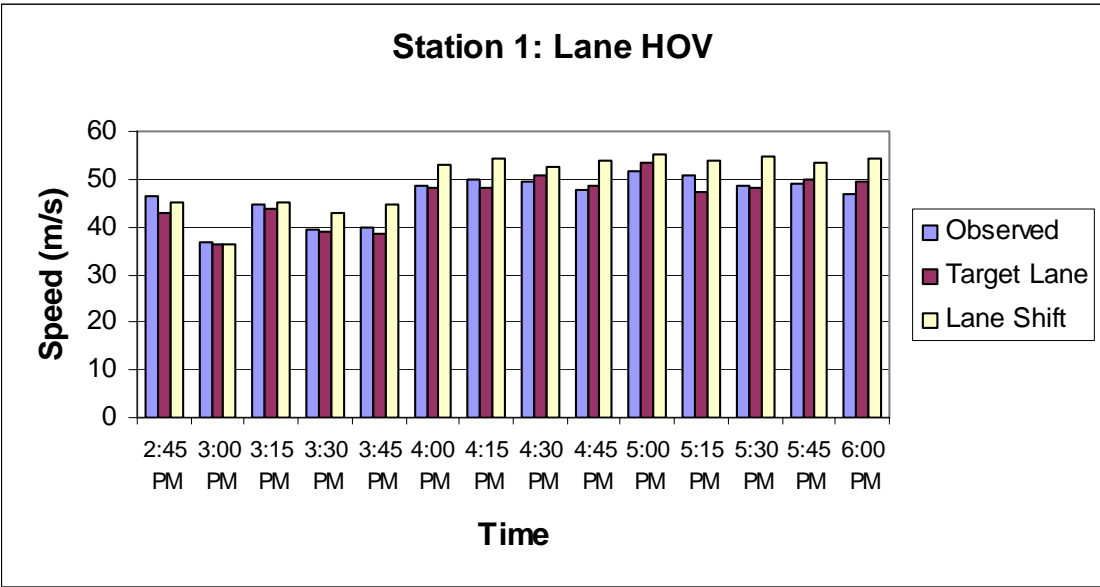
Variable	Parameter value	t-statistic
Car following acceleration		
Constant	0.027	0.45
Speed, m/sec.	0.364	0.83
Space headway, m.	-0.167	-2.72
Density, veh/km/lane	0.571	2.00
Relative speed, m/sec.	0.525	8.18
$\ln(\sigma_{cf, acc})$	0.131	12.92
Car following deceleration		
Constant	-0.830	-1.65
Space headway, m.	-0.561	-9.49
Density, veh/km/lane	0.152	0.92
Relative speed, m/sec.	0.825	12.78
$\ln(\sigma_{cf, dec})$	0.155	15.14
Free-flow acceleration		
Sensitivity constant	0.079	10.64
$\ln(\sigma_{ff})$	0.183	11.86
Desired speed		
Constant	17.546	55.81
Heavy vehicle dummy	-1.345	-1.07
Reaction time distribution		
Constant	-0.124	-1.90
$\ln(\sigma_{\tau})$	-0.121	-1.05
Headway threshold distribution		
Constant	2.574	45.78
$\ln(\sigma_h)$	-0.807	-8.41

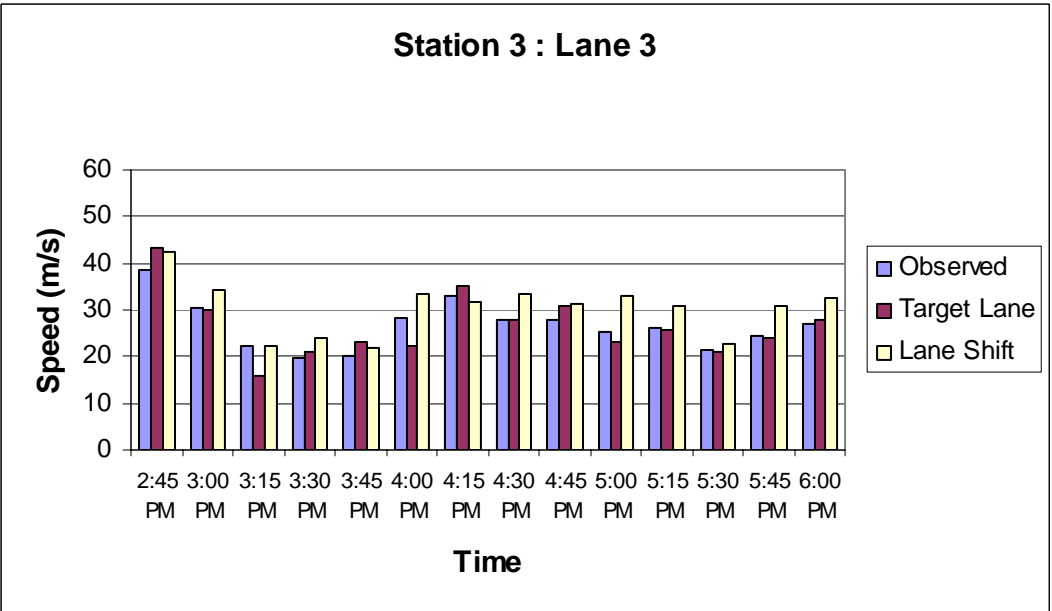
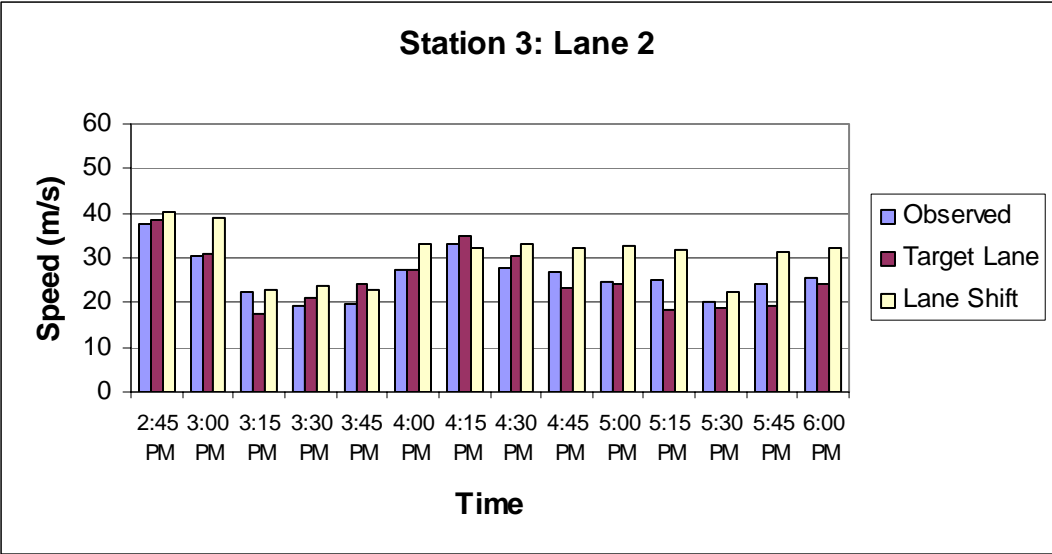
Appendix B

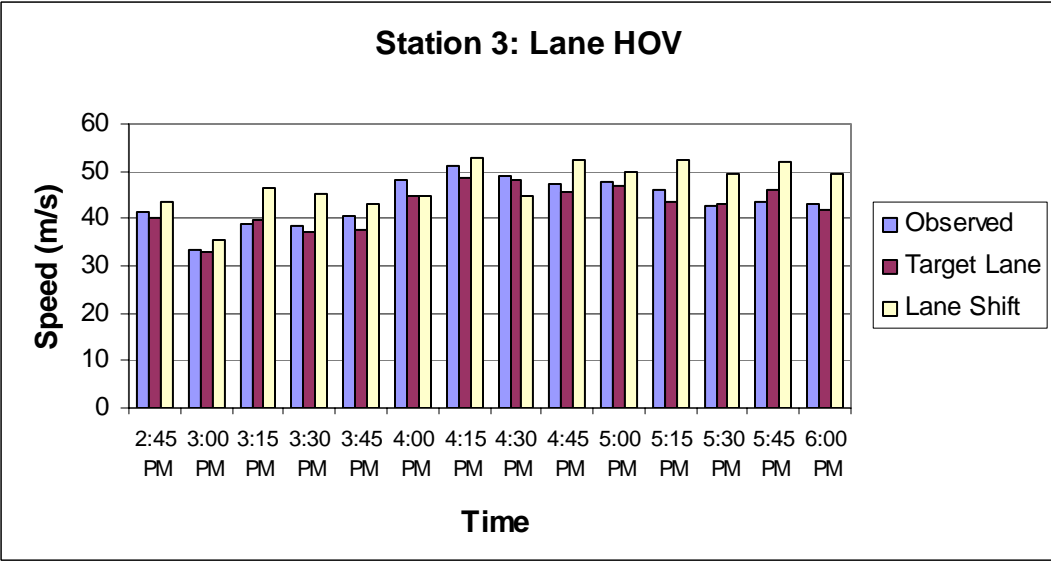
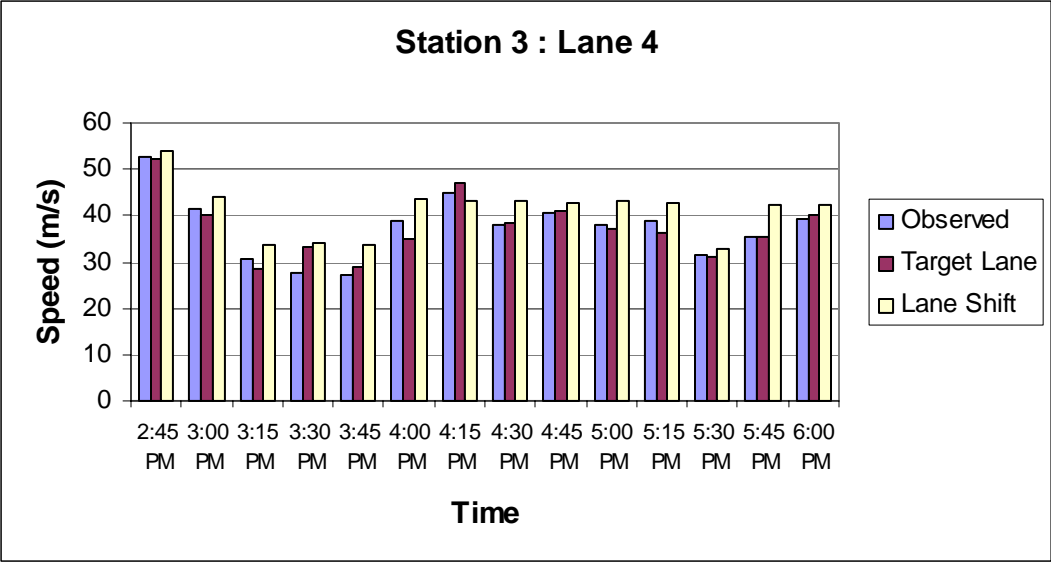
Plots of Observed and Simulated Lane-Specific Sensor Speeds

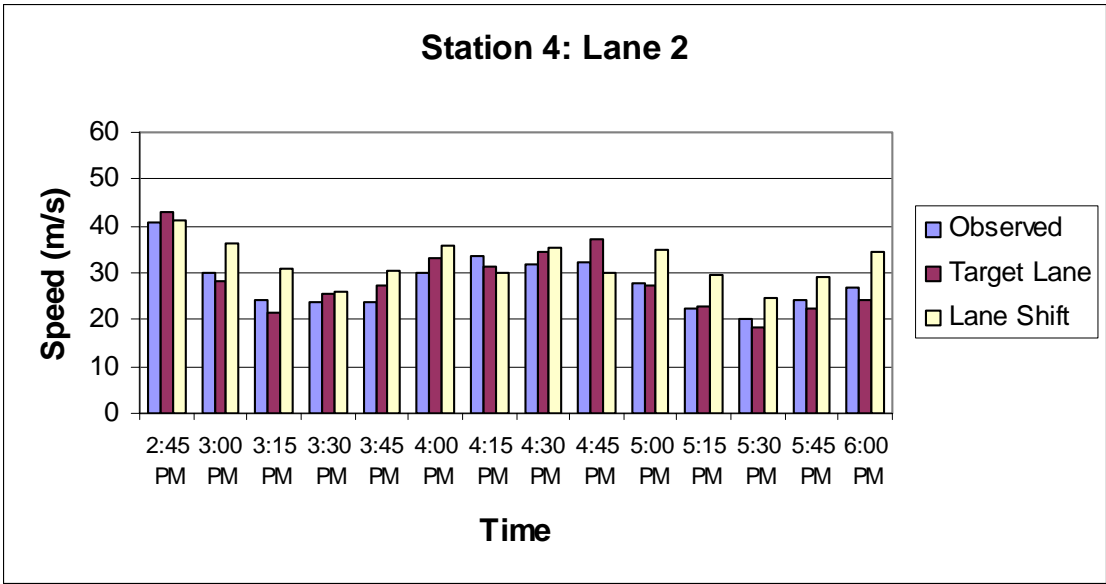
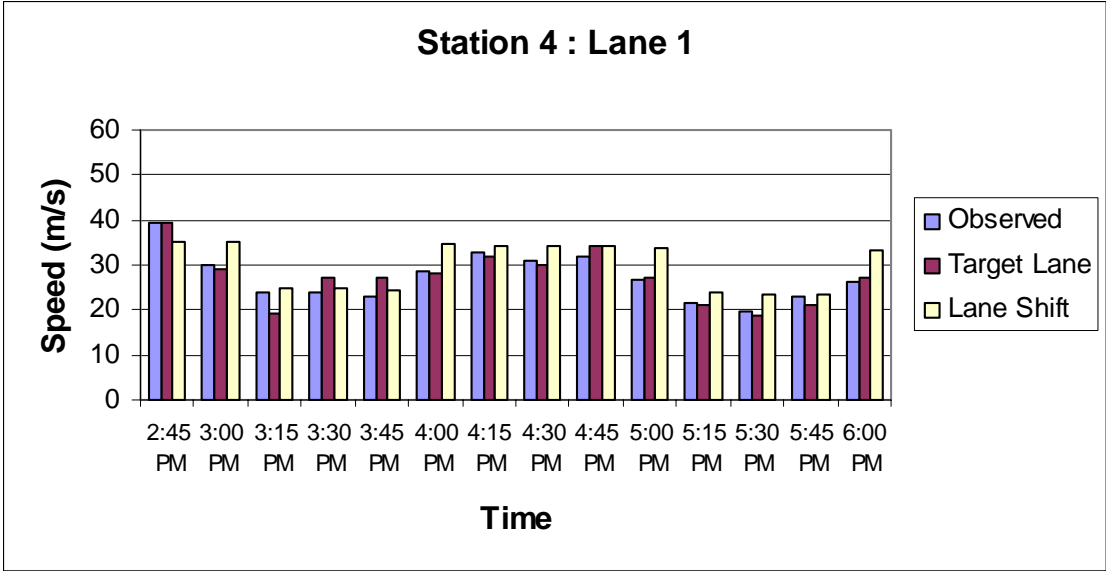


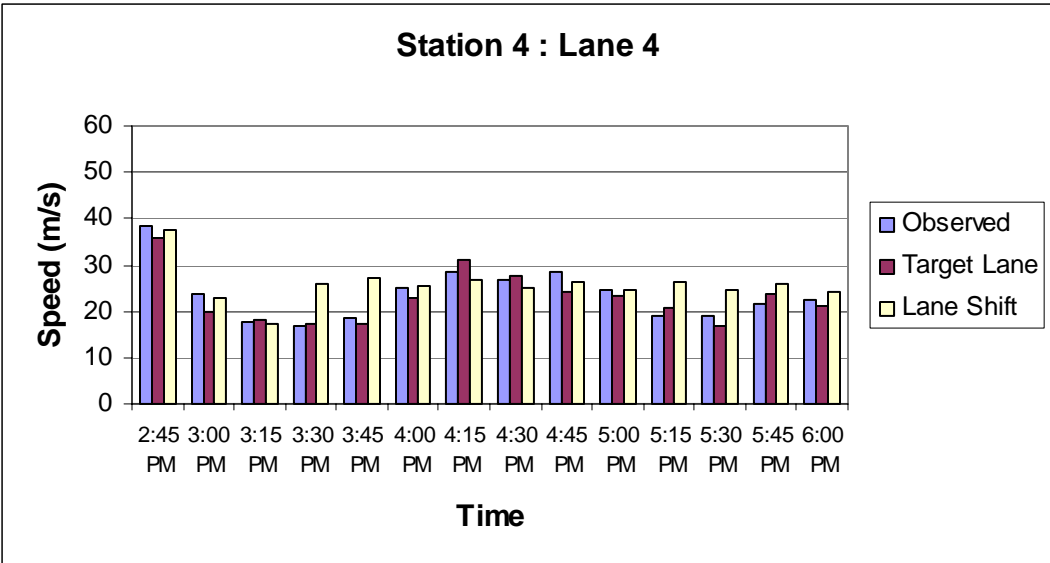
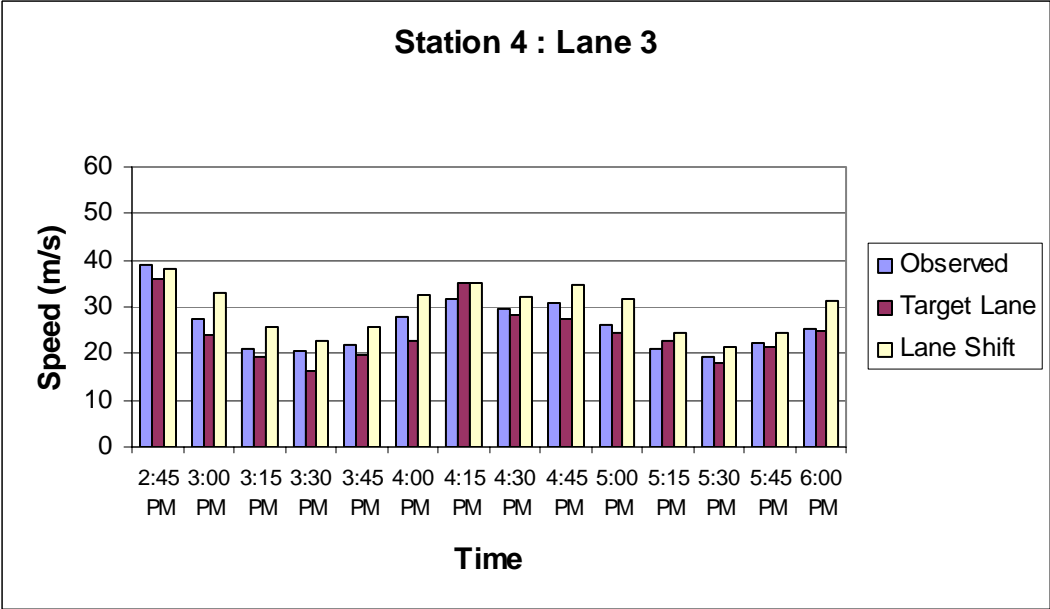


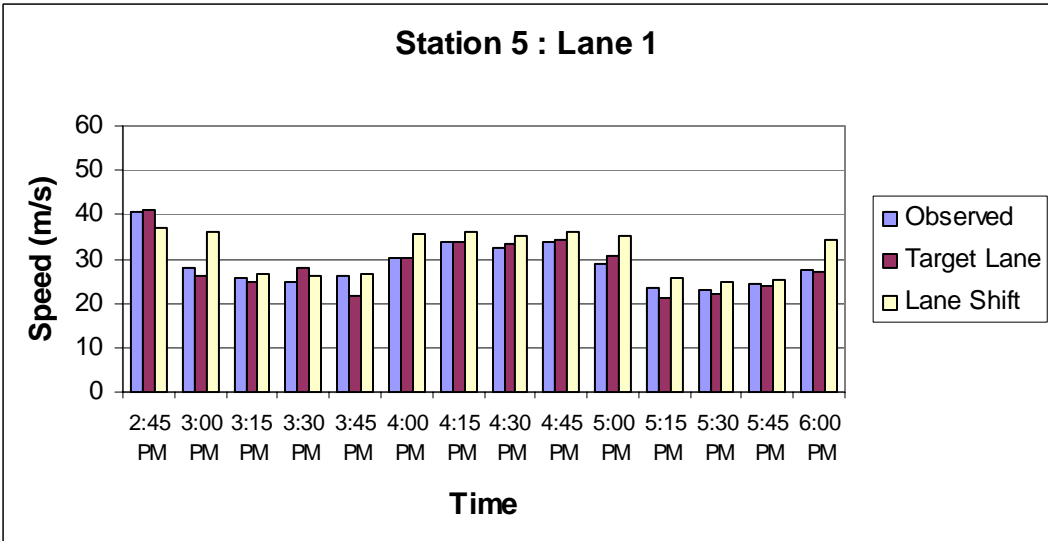
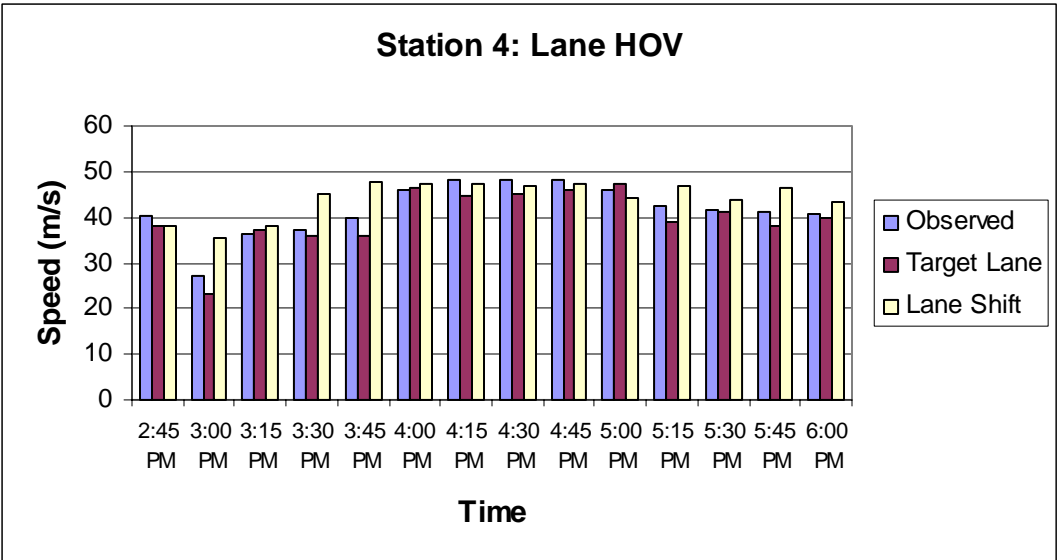


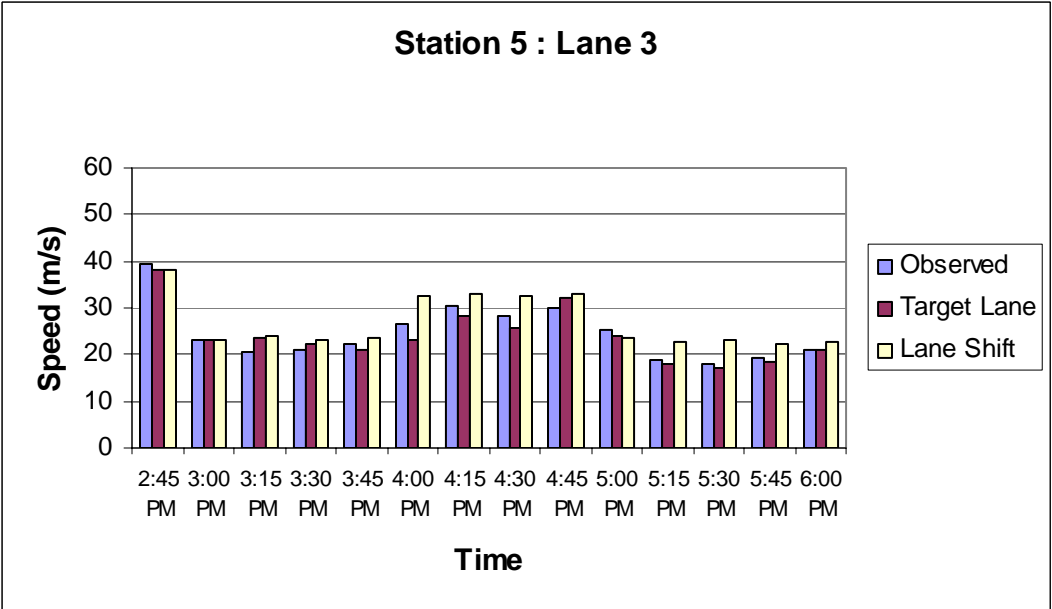
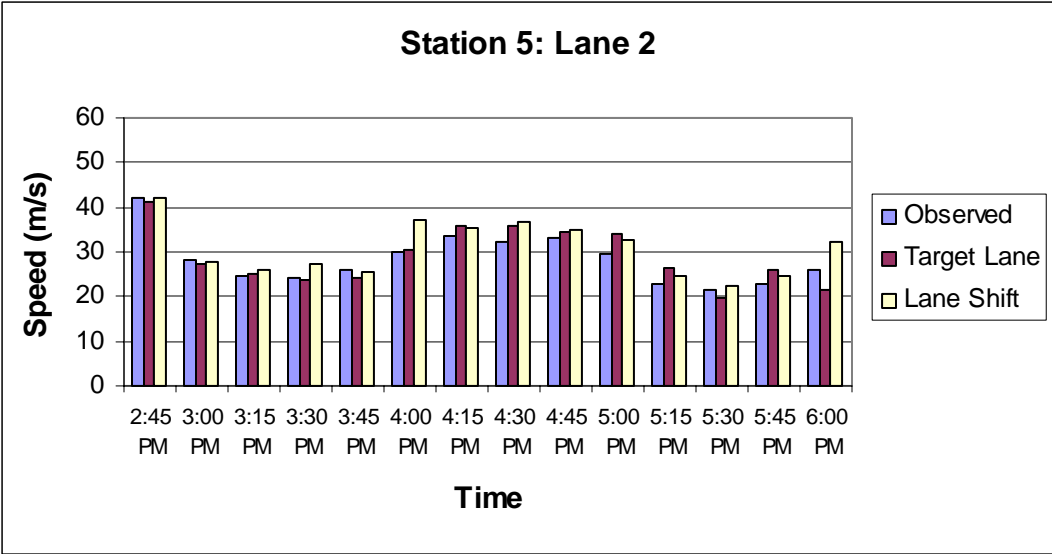


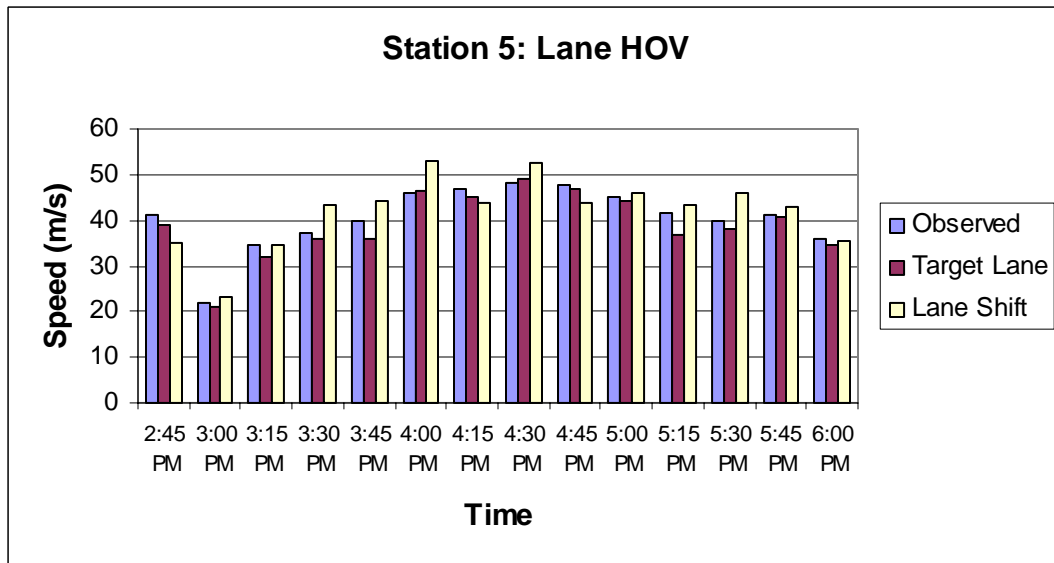
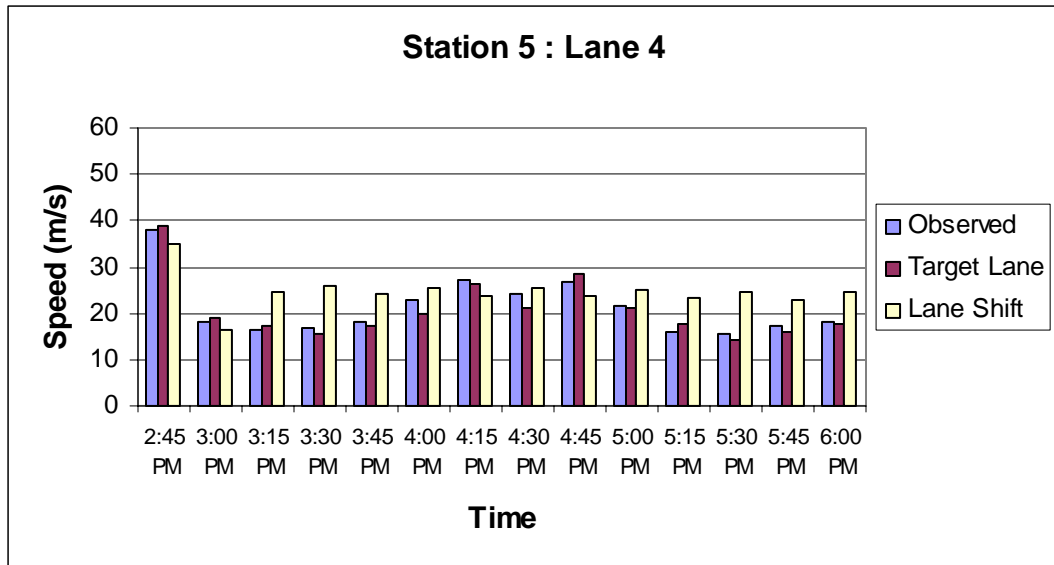


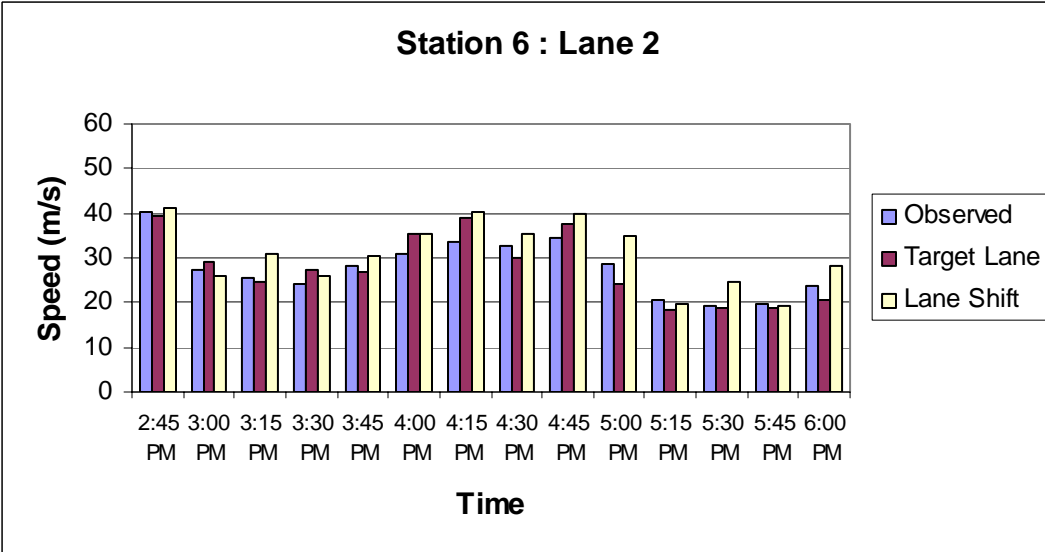
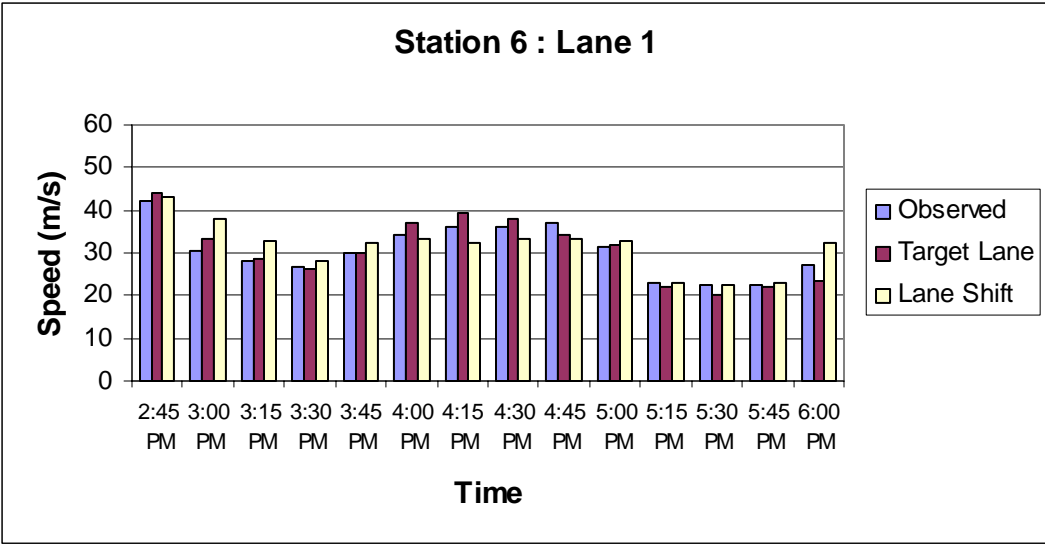


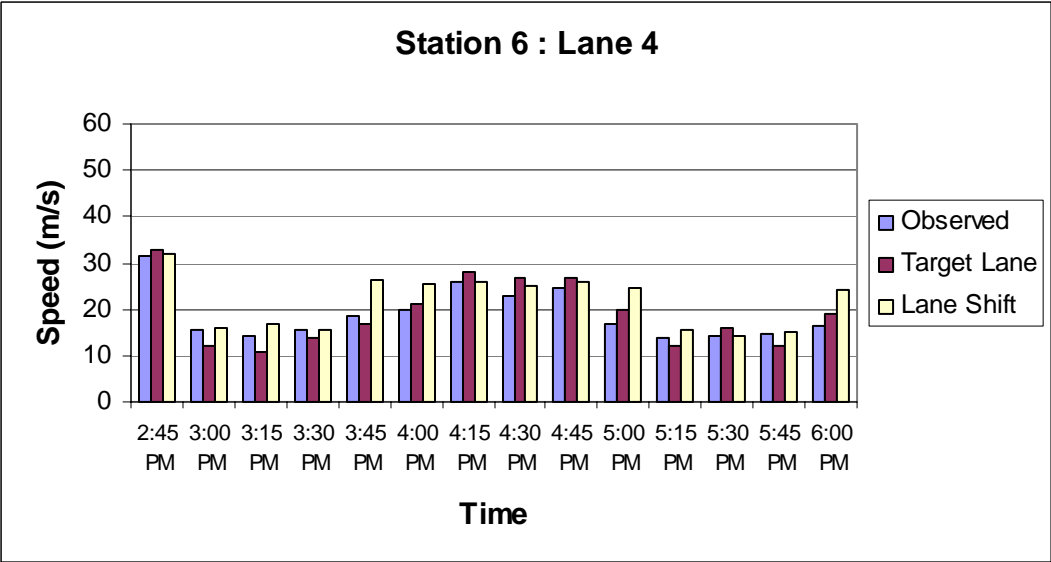
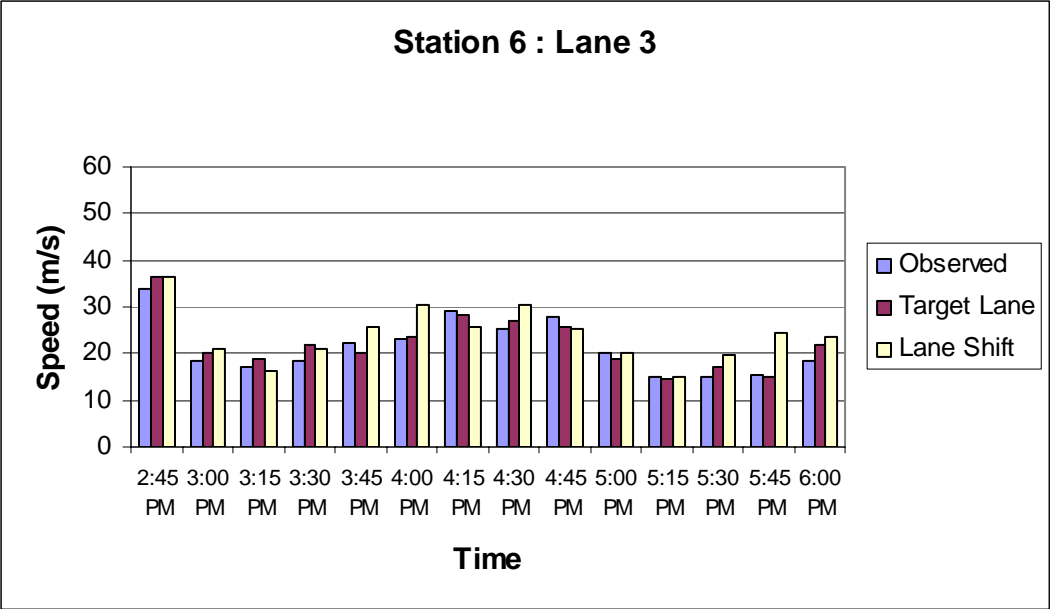


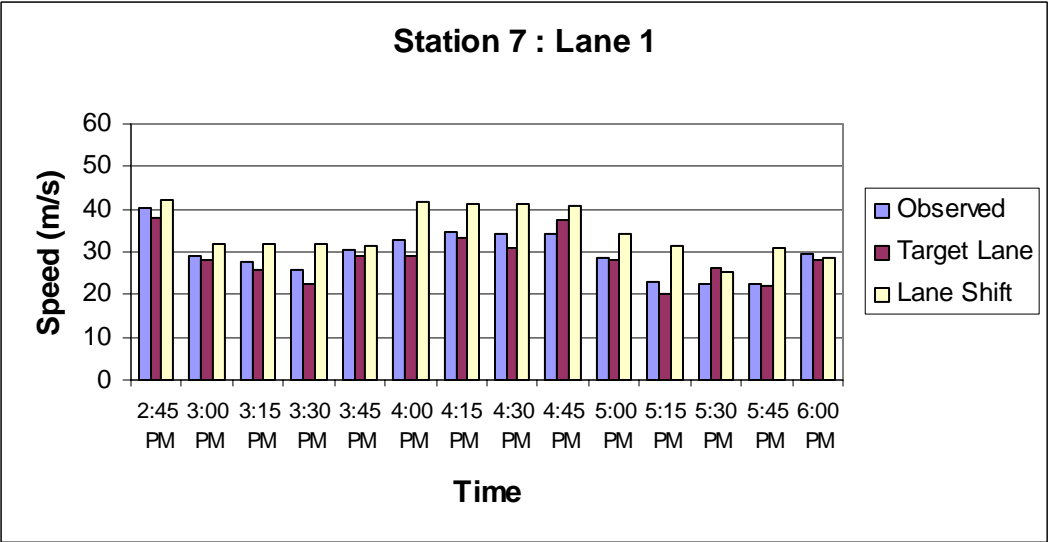
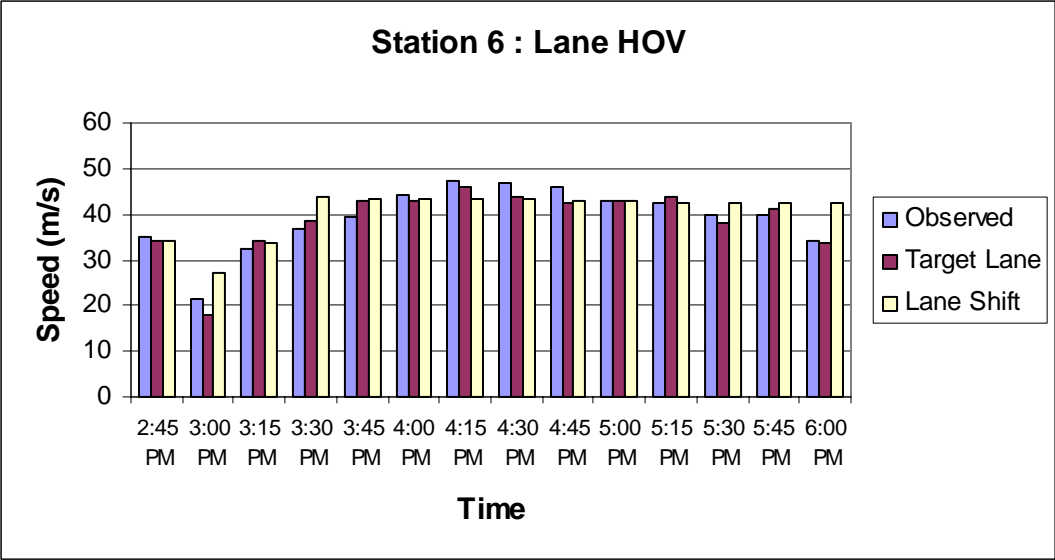


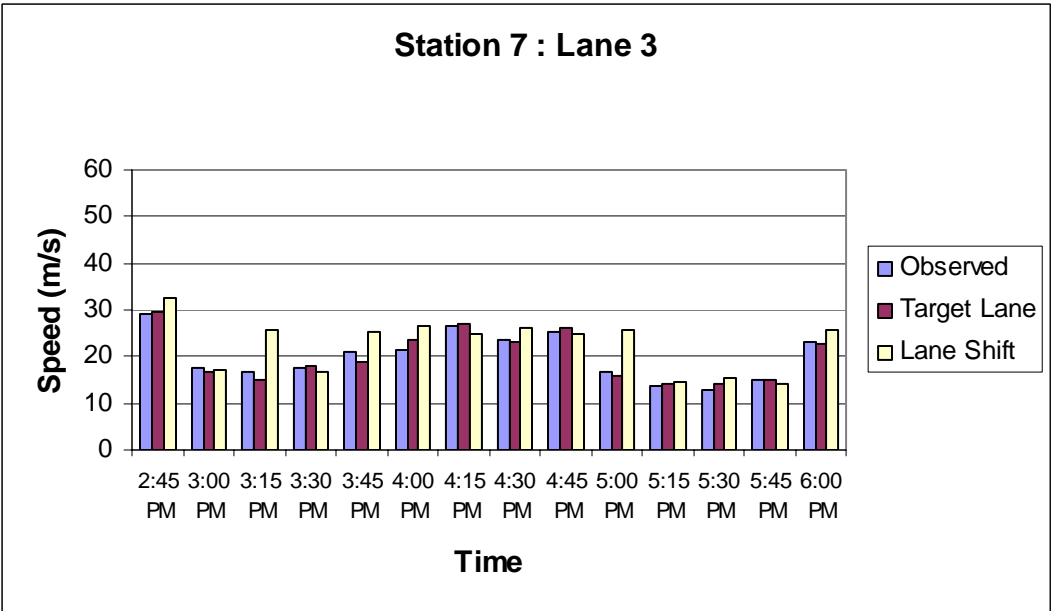
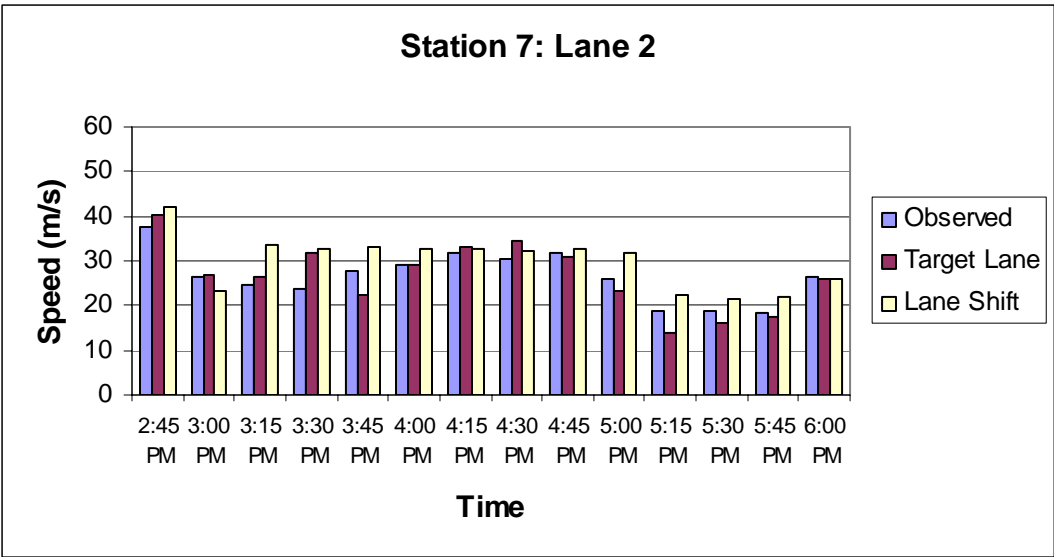


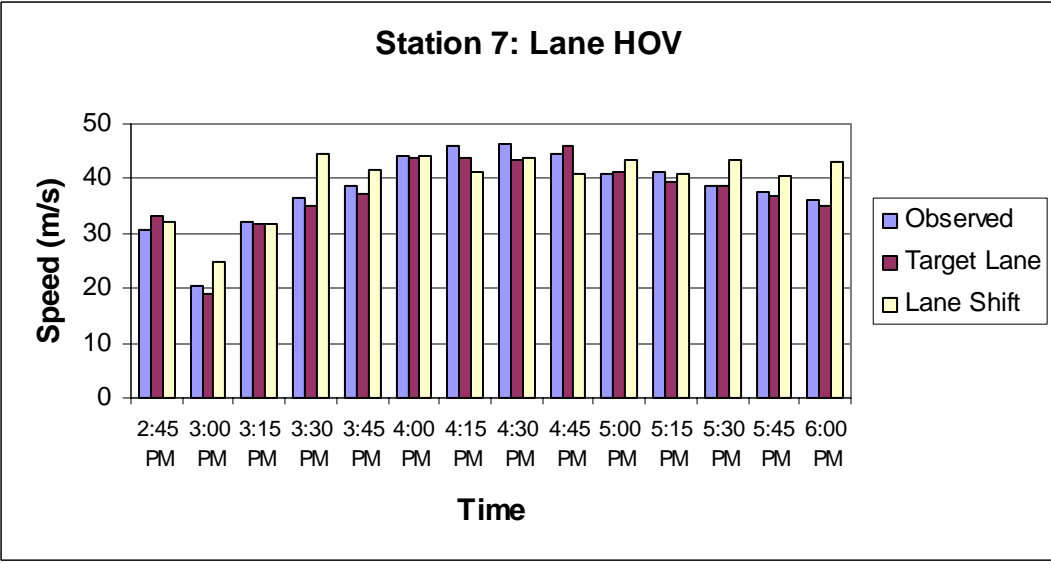
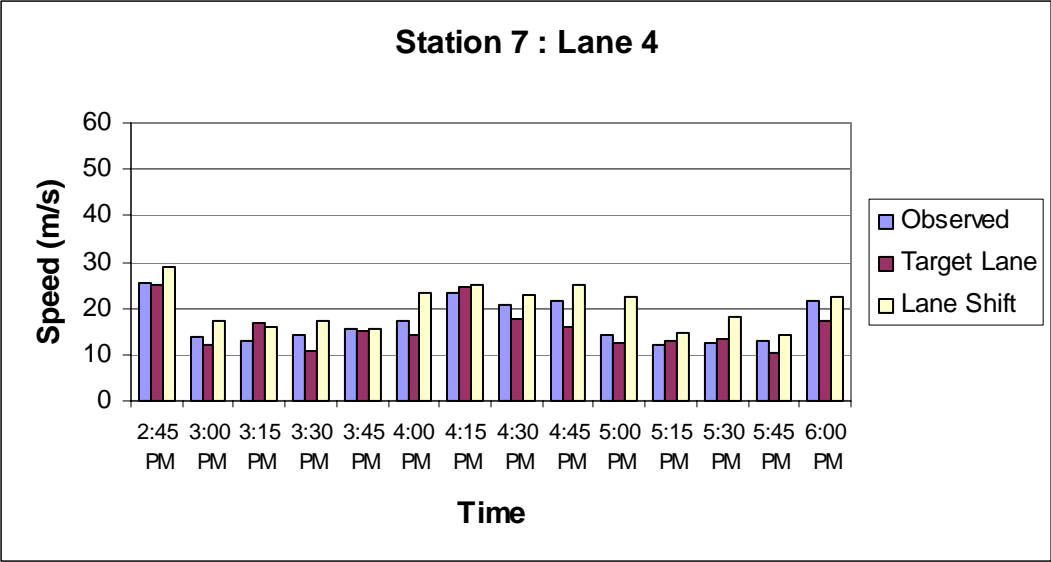












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