Modeling Influencing Factors in a Microscopic Traffic Simulator

by

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B.S. in Civil Engineering (2002)
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Submitted to the Department of Civil and Environmental Engineering
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Abstract

Microscopic traffic simulation is an important tool for traffic analysis and dynamic traffic management as it enables planners to evaluate traffic flow patterns, predict and evaluate the outcome of various response plans and assists in decision making. It is a vital tool for traffic management centers and can be helpful in developing contingency plans to enhance the safety and security of the transportation system.

This thesis investigates the current state-of-the-practice in traffic microsimulation tools. A survey was developed and administered to developers. Results of the survey indicate critical gaps in including influencing external factors beyond the interaction of vehicles, such as incidents, work zones, or inclement weather, in traffic simulators. This thesis introduces a framework for incorporating such factors in existing models. The nature of the influencing factors limits disaggregate trajectory data collection generally needed to estimate driving behavior models. Therefore, an approach using aggregate calibration to refine and enhance existing driving behavior models is formulated.

The aggregate calibration methodology is illustrated with a case study incorporating the effects of weather in driving behavior models using a freeway corridor in the Hampton Roads region of Virginia. MITSIMLab, a microscopic traffic simulation laboratory that was developed for evaluating the impacts of alternative traffic management system designs at the operational level, is used for evaluation. The presence of precipitation was found to be significant in reducing speeds in the case study and was incorporated into the driving behavior models with aggregate calibration. This methodology was found to improve the simulation results, by reducing bias and variability. Assessment of the approach is discussed and recommendations for improvement and further study are offered.

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Chapter 1

Introduction

1.1 Motivation

Accessibility and mobility are the key functions of transportation systems. Accessibility is the ability to reach desired goods, services, activities and destinations. Mobility is the movement of people and goods. Restrictions to accessibility and mobility, which can result from traffic congestion, natural disasters, or terrorism, for example, have a profound impact on the national economy, quality of life, and the nation's safety and security. Intelligent Transportation Systems (ITS) and transportation analysis tools allow us to understand disruptions in transportation systems, predict effects, and therefore, mitigate the impacts of such events.

Traffic congestion levels have increased in both large and small urban areas since 1982, affecting a larger portion of the day, more roads and more travel and causing increased costs to users. The Texas Transportation Institute (TTI) estimates that in 2001 the average cost of congestion effects per person was $520, ranging from $650 in very large metro areas to $130 in small areas (Schrank and Lomax, 2003). Additionally, the TTI study estimated that the average person experienced 26 hours of delay and wasted 42 gallons of fuel. These figures result in a total cost of $69.5 billion in cost, 3.5 billion hours of delay and 5.6 billion gallons of wasted fuel in 2001 (for the 75 study areas). These figures showcase the adverse effect of congestion on the economy, quality of life and the environment. Commercial vehicle operations are even more heavily impacted by congestion and inclement weather as travel delay disrupts the entire supply chain. Weather-related delay adds $3.4 billion in costs on freight operations alone (Row, 2003).

By providing accessibility, transportation networks are a natural target for terrorism, as September 11th so horrifically demonstrated. Paradoxically, the very target can also provide safety and security. The terror in New York City could have been exponentially worse had transportation operators and analysts not used the system to their advantage to move millions of people efficiently out of the city and to prevent people from entering the danger zone. Even when an incident does not directly affect transportation, the transportation system is impacted. Transportation is the means by which responders get to the scene, citizens escape a hazard and victims are moved to safety. Effective, efficient evacuation is inextricably linked with the transportation. A critical component of U.S. homeland security is contingency and evacuation planning.

Figure 1-1 graphically presents a risk continuum for a sample of the diversity of incidents that impact the transportation system as presented by Vince Pearce of FHWA (2004). Traffic accidents occur on a daily basis and have relatively low impact (per event) on the system when compared to natural disasters or acts of terrorism. Because accidents happen so frequently, there is increased knowledge about their impacts and more experience in managing them. However, when rarer incidents such as natural disasters or acts of terrorism occur, the consequences can be devastating to the transportation system and the community. It is vital for security and safety to be prepared in order to minimize the consequences with contingency planning.

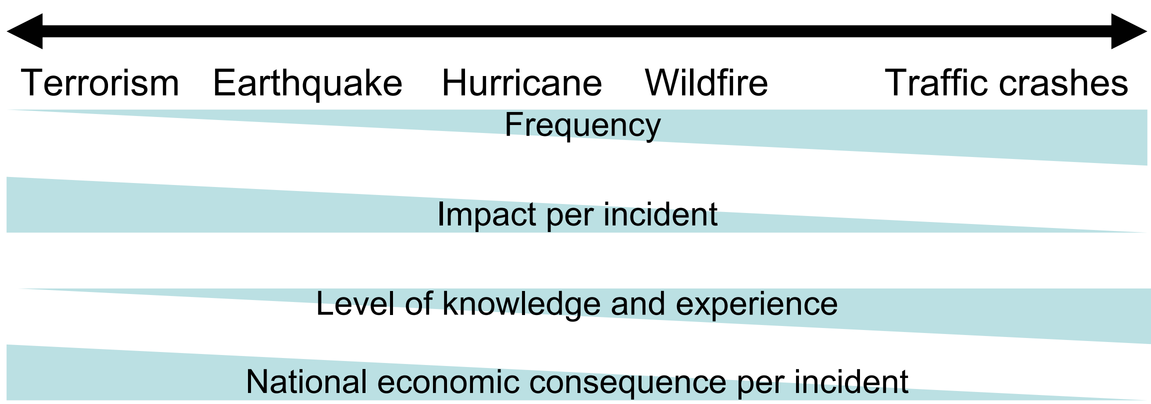

Figure 1-1: Risk Continuum of Incidents Affecting Transportation

Developing a safe, efficient, and redundant transportation system is critical. This goal can be facilitated by applying the appropriate Intelligent Transportation Systems and information technologies. Applications of ITS, systems that collect, store, process and distribute information relating to the movement of people and goods, have become effective tools for traffic management and have demonstrated the ability to provide remedial measures for traffic congestion and options for improving traffic operations. Microscopic traffic simulation is an important tool for traffic analysis and dynamic traffic management as it enables the user to evaluate traffic flow patterns, predict and evaluate the outcome of various response plans and assists in decision making. It provides a useful environment in which to test the effectiveness of various technologies, configurations or changes to the network. It can be used for both long-term planning operations, as well as for shorter-term incident or emergency management strategies/plans. Real-time tools enable traffic management operators to be proactive, minimizing the disturbance to the system, rather than reactive in response to congestion or incidents.

Traffic and transportation analysis tools are a perfect example of effective dual-benefit technologies advocated by ANSER (Advancing National Strategies and Enabling Results), a public service research institute that provides support to federal agencies for homeland security. Dual-benefit solutions are those that enhance the security of our nation while advancing some other public good, Enhancing transportation analysis tools not only provides daily benefit for commuters - by simulating field conditions, enabling more efficient traffic management and providing better information, but it enables traffic management centers to be prepared in case of destruction (intentional or not) to the critical parts of the system and to plan for and execute efficient and safe evacuations.

However, the effectiveness of microscopic traffic simulation tools depends on the integrity of their underlying behavioral models. The Federal Highway Administration (FHWA) has found this topic and simulation tools to be so valuable that they have developed the Next Generation Simulation (NGSIM) program, which aims to improve the quality and performance of simulation tools, promote the use of simulation for research and application, and achieve wider acceptance of validated simulation results. Within these goals, the program's objectives are to develop a core of useful and open behavioral models in order to enhance the state-of-the-art of behavioral traffic models and advance the state-of-the-practice of the traffic simulation models used by traffic professionals.

Clearly, the foundation for developing effective and accurate driving behavior models is understanding which factors impact driver decisions, behaviors and movements. Much of this is known from a large-scale systems perspective; conditions that cause congestion, accidents and delay impact driver behavior. When events that are an aberration from the norm occur, it is more difficult to predict driver response and thus, the extent of the consequence of such an event.

This can be supported by the fact that the primary cause of freeway congestion is a result of the temporary loss of capacity due to non-recurring events. The three main causes of non-recurring congestion are incidents, work zones, and weather. Crashes were estimated to cause almost 40% of non-recurrent delay in an Oak Ridge National Laboratory (ORNL) study (Chin, et al, 2002). A significant portion of incidents occurs under adverse road conditions, for example in the presence of rain, snow, sleet, fog, wet pavement, snowy pavement, slushy pavement or icy pavement. In 2001, more than 22% of vehicle crashes were weather related, with most occurring when the pavement was wet or during rainfall (Goodwin, 2003). Additionally, the inclement weather has significant adverse effects on mobility and productivity. While flooding and snow accumulation result in clear capacity reduction of the roadway, even light rain and wet pavement reduces capacity and increase travel time. The ORNL study also estimates that 27% of the non-recurrent delay on freeways is due to snow, ice and fog, which reduce visibility and/or traction (Chin, et al, 2002).

Further, a key way in which non-recurring congestion affects travel is the distinction between mobility, the ease of getting to a destination, and reliability, the predictability of travel times for trips. These factors are clearly linked. Recurring congestion, which occurs simply when the demand for the roadway exceeds its capacity, reduces mobility daily. Nonrecurring events, or temporary disruptions, dramatically reduce the available capacity and reliability of the entire transportation system. When uncontrollable events such as incidents and inclement weather events are large factors in capacity reduction, the ability to accurately predict travel times in these instances is critical. Travelers and freight operators are particularly sensitive to unanticipated disruptions to tightly scheduled personal activities and manufacturing distribution procedures. As a result, improved reliability is highly valued by travelers. Additionally, how drivers respond to improved reliability and traffic information influences mobility.

Though there is knowledge of overall system effects, there is a deficiency in understanding of driver-level, microscopic response to such influencing factors. Current transportation analysis tools are lacking representation of many of these factors that influence traffic congestion and driving behavior. This thesis attempts to identify these deficiencies and develops an approach to include them in transportation analysis tools. The next chapter presents a detailed analysis of the existing capabilities of microscopic traffic simulators in modeling key factors that contribute to non-recurring congestion (incidents, weather and work zones), and also more fundamental factors, including network geometry, traffic control, vehicle interactions, and traveler information.

1.2 Objectives

The objective of this thesis is to develop a framework for modeling key influencing factors in microscopic traffic simulation tools. The motivation for improving transportation analysis tools described above provides several limitations in existing traffic management and planning capabilities. This research aims to explore these limitations in more detail and identify critical gaps in existing models and microscopic traffic simulation tools. An approach of enhancing existing driving behavior models to include external factors with available aggregate data will be developed and applied with a case study in a Microscopic Traffic Simulator (MITSIMLab). The critical gaps identified and aggregate model approach should provide motivation and direction for future research.

This thesis contains two key contributions. To assess the current state-of-the-practice in microscopic traffic simulation a survey was designed and administered to developers of simulation tools considered to be industry leaders. The results of this survey are summarized in Chapter 2. Based on responses from the developers, it is clear that there is a systematic limitation of simulation tools regarding incorporating the impact of external factors on driving behavior. The results of this survey and identification of the recurring omission of factors that literature has shown to be important provided a motivation to develop a methodology to incorporate such factors. Given the nature of the critical influencing factors and limited data available to model them, an aggregate calibration approach was then investigated and tested with a case study. A general calibration framework was modified to incorporate the external factor into existing driver behavior models. One of the critical external effects, weather, was used to test the methodology.

1.3 Thesis Outline

The remainder of this thesis is organized in five chapters. Chapter 2 presents background information, including a literature review and survey results reporting the state-of-the-practice in treatments of influencing factors on driver behavior. These results reveal the need to incorporate such factors into microscopic traffic simulation tools and driving behavior models. Chapter 3 introduces a framework to calibrate driving behavior models and highlights an approach specifically for external factors. Due to the nature of these influencing factors and limitations of data, an aggregate calibration methodology is featured.

An application of the methodology is described in Chapter 4, where the study area in Hampton Roads, Virginia is introduced. Within this chapter, motivation to use weather to test this approach is discussed along with a description of the data available. The simulation environment used, MITSIMLab, and its driving behavior models are also introduced. Results of the case study, including origin-destination estimation and driving behavior parameter calibration are presented in Chapter 5 and conclusions and directions for further research are summarized in Chapter 6.

Chapter 2

Background and Literature Review

This chapter summarizes the state-of-the-practice in treatments of influencing factors on driver behavior. Examples of influencing factors include network geometry, work zones, incidents, traffic control and information, and environmental features such as adverse weather conditions. System state – the relation between a traveler and other travelers captured by their spacing, relative speed, and other variables – is not covered in this review, although it is well-known to be a significant contributor to changes in travel and driving behaviors.

Twelve state-of-the-art microscopic traffic simulation software tools were identified as industry leaders in traffic simulation. Developers of these tools were invited to respond to a questionnaire entitled, Influencing Factors in Microsimulation (Appendix A). The purpose of this survey was to identify the parameters and mechanisms used by existing simulators to capture the effects of external factors and conditions on driving behavior. The questionnaire, and this chapter is divided into eight sections, dealing with the representation of five categories: 1) network, 2) system management, 3) environment, 4) traveler characteristics, and 5) vehicle characteristics. Using the survey results, the status of individual factors was examined and an assessment of the gaps in simulation modeling was performed. The survey was developed and administered as part of the NGSIM Program and the results have been included in the *NGSIM Task E.1-1: Core Algorithm Assessment*, prepared for the Federal Highway Administration (Cambridge Systematics, 2004).

Each subsection presents a table summarizing existing simulation capabilities with respect to influencing factors. These tables detail – for each influencing factor – the number of systems, out of the twelve that were surveyed, that represent the factor and at what level its effect on behavior is captured: explicitly (direct), using proxy methods (proxy), or not at all (none). Note that in many cases, a factor may be included but have no effect on behavior. For example, several simulation systems can animate vehicles traveling on curved roads, but the behavior of drivers is not different because the road is curved. Therefore, there may be instances where the factor is included in the system data but not utilized in the behavioral model. Alternatively, a factor that is not explicitly included may be simulated using a proxy approach that does affect driver behavior. For example, several systems imitate inclement weather conditions by changing link characteristics such as speed distributions or speed limit.

Table 2-1: Survey Participants

Product	Organization
AIMSUN	Transport Simulation Systems
ARTEMIS	University of New South Wales
CORSIM	FHWA
Cube Dynasim	Citilabs
DRACULA	University of Leeds
INTEGRATION	Virginia Tech University
MITSIM	Massachusetts Institute of Technology
Paramics	Quadstone
SimTraffic	Trafficware
TransModeler	Caliper Corporation
VISSIM	PTV
WATSim	KLD Associates

Additional summary tables present an evaluation of the status of influencing factors on the three primary behavioral models, which are common to most simulations reviewed. These models are acceleration (an operational behavior); lane-changing (a tactical behavior); and route modification (a strategic behavior). These tables use symbol to evaluate the state-of-the-art: full circle (●) entries indicate that the specific influencing factor is explicitly represented in current systems; split-circle (∅) entries indicate that only proxy substitute methods are used; hollow circles (○) indicates that the influencing factor is not currently represented in existing systems; and empty entries indicate that the impact of the influencing factor on the behavior in question is marginal or unimportant.

This section does not directly evaluate the quality of the implementations or models; rather, it is an inventory of existing simulation capabilities at the aggregate level of implementation (explicit, proxy, or none). Therefore, it is not necessarily accurate that an influencing factor represented explicitly in the majority of the simulation systems surveyed represents that the factor is unimportant for further study.

2.1 Network

This section discusses the two main elements of network-related influencing factors, characteristics of links and characteristics of intersections.

2.1.1 Link Geometry

Network geometry has a direct effect on driver behavior. At the aggregate level, these effects have been studied extensively. For example, the various models within the Highway Capacity Model (HCM, 2000) predict levels of service and capacities of different road facilities and contain adjustment factors for lane width, median type (highways) and lateral clearance. One example of a more direct connection of network elements to microscopic traveler behavior is the fact that perception – reaction time, which is a factor in braking and lane changing, is affected by sight distance (McShane, et al., 1998). Additionally, acceleration capabilities and braking distance are affected by grade changes. Table 2-2 presents a summary of the influences of link geometry on behaviors.

Table 2-2: Link Characteristics

Influencing Factor	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Horizontal curves	12		1	7	4
Facility type	12		4	5	3
Lane widths	9	3		3	9
Median characteristics	7	5	1		11
Shoulder characteristics	7	5	1		11
Grade & grade changes	12		12		
Pavement quality	1	11	1	3	8
Auxiliary lanes	11	1	7	1	4
Route restrictions/lane use	11	1	8		4
Sight restrictions	5	7	5	3	4

Horizontal curves and facility type are represented in all of the systems surveyed, but the effects on driver behavior vary. While horizontal curves are purely geometric features with no effect on behavior in a few systems, others (ARTEMIS, CORSIM, CubeDynasim, DRACULA, MITSIMLab and WATSIM) have user-defined maximum speed for each arc or curve, which can affect acceleration. VISSIM allows the user the option of defining the curve as a slow moving zone, which requires vehicles to decelerate before and accelerate after the curve, and a cost that would penalize it in the route choice model. Horizontal curves affect the car following model in INTEGRATION. In Paramics, the vehicle automatically reduces speed, dictated by radius of the curvature, the frictional effects, and the vehicle characteristics. Similarly, facility type (primarily urban, freeway, and rural or user-defined classes) does not affect driver behavior in some systems. However, in most systems (CORSIM, DRACULA, TransModeler, VISSIM, and WATSIM) acceleration and lane changing are explicitly affected by road type characteristics. Facility type is included as a parameter in the car-following model in INTEGRATION, while it affects lane changing and route choice in Paramics. MITSIMLab includes a freeway bias parameter in the route choice model, which captures driver preference to drive freeway routes over non-freeway routes. CubeDynasim contains link types for single lanes, multi-lanes, weaving areas, and lane shifts, etc. that effects lane changing and route choice.

Eight of the systems explicitly represent lane widths, but it only affects driver behavior in VISSIM, which allows the lane width to be linked to a slow speed zone (i.e., if the lane width is less than ten feet, a different desired speed distribution is used). The lane width is only used for graphical display in MITSIMLab and other models. Typically a proxy approach is available to simply divide the link into segments and modify the speed limit and free-flow speed.

Although seven of the systems represent shoulders, they only affect the acceleration model in INTEGRATION. Within the TransModeler on-street parking model, vehicles entering and leaving parking spaces affect the acceleration and lane-changing behaviors of vehicles upstream.

All systems explicitly represent grade and grade change, which directly affects vehicle acceleration. Pavement quality is only explicitly represented in CORSIM (FRESIM) with a friction coefficient that affects the maximum speed on horizontal curves. Eleven systems represent auxiliary lanes. Within those, lane-changing behavior (and indirectly, acceleration) is affected in CORSIM, CubeDynasim, DRACULA, MITSIMLab, Paramics, TransModeler, and VISSIM.

Eleven of the systems explicitly contain route restrictions or lane use privileges, which affect lane changing behaviors and route choice (for those systems that incorporate route choice). Vehicles are required to change lanes if they are not allowed in a specific lane or are prohibited from entering it (i.e., HOV/bus lanes) and are not allowed to choose paths that are restricted to them.

Five systems explicitly represent sight restrictions – CORSIM and DRACULA apply sight restrictions to lane changing movements while MITSIMLab and SimTraffic have visibilities of sight distance associated with control devices, which may affect both acceleration and lane changing. Similarly, CubeDynasim allows user-defined visualization zones at each conflict point. Several other systems represent sight restrictions by proxy, using speed distributions and maximum free-flow speeds.

2.1.2 Intersection Geometry

Table 2-3 below summarizes current simulation capabilities with regard to intersection characteristics.

Table 2-3: Intersection Characteristics

Influencing factor	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Angle between links	11	1	7	2	3
Flared lanes (slightly wider lanes at intersections allowing right turns without a full turning pocket)	12		8		4
Traffic calming static obstacles	6	6	3	5	4

Eleven of the systems represent the angles between links, and in most it affects acceleration and lane-changing. AIMSUN and VISSIM also incorporate turn penalties, which affect route choice. All systems contain flared lanes, which affect lane-changing as some vehicles must move into the bay to complete the desired turn. Only three (AIMSUN CubeDynasim and TransModeler) of the systems explicitly can represent traffic calming obstacles, which affects acceleration due to reduced speeds and implicitly affects route choice as travel time on those links is increased. Five other systems (ARTEMIS, DRACULA, MITSIMLab, Paramics, and VISSIM) represent traffic calming via a proxy approach by locally modifying maximum speed and/or desired speeds.

2.1.3 Evaluation

The various elements of the geometric design of the roadway are core factors affecting driver behavior. Table 2-4 presents a summary of these network factors in relation to key behaviors.

The presence and the properties of curves and grades, medians and shoulders, lane width and pavement quality as well as the design of intersections and traffic calming devices affect both acceleration and lane-changing behaviors. These factors, perhaps to a lesser degree, also affect route choice behavior. For example, a driver may prefer to use highway facilities compared to surface streets or avoid roads with poor pavement quality; flared lanes and lane-use restrictions may force drivers to change lanes or select routes that they would otherwise not choose.

Table 2-4: Best Practices of Important Network Effects

Influencing Factor	Acceleration	Lane-Changing	Route Modification
Horizontal curves	∅	○	
Facility type	∅	○	●
Lane widths	∅	∅	●
Median characteristics	∅	○	
Shoulder characteristics	∅	○	
Grade & grade changes	●	○	○
Pavement quality	∅	○	○
Auxiliary lanes		○	
Lane restrictions		●	●
Sight restrictions	∅		
Angle between links	∅		∅
Flared lanes			
Traffic calming	○		○

The treatment of these factors in simulation systems is limited. In most cases, the effect of geometric characteristics is captured by proxy mechanisms such as defining slow moving zones or dividing links in different segments with different properties. These mechanisms allow the user to modify factors such as the means and distributions of maximum speeds and desired speed. While this may affect acceleration behavior directly, the impact on lane-changing is only indirectly captured. Limiting maximum or desired speeds suffices in uncongested traffic conditions, but is of little impact in congested conditions, where the interactions between neighboring vehicles and network conditions play a subtler role in behavioral models. To illustrate this point, consider a section with narrow lanes. It is expected that traffic speed and capacity in that section would be reduced, which – under uncongested regimes – it is. Under congested regimes, however, the behavioral effects are subtler. Some drivers may be more inclined to stay in their lanes and, therefore, less likely to change lanes. Other vehicles may occupy space on two lanes, and so, reduce capacity even further. Under existing modeling approaches, these subtleties are not modeled and may overestimate capacity of such sections.

2.2 System Management

2.2.1 Traveler Information

There have been many studies of drivers' response to traveler information, including the effect of various types of information provided on route choice, as well as the benefits gained in both recurring and non-recurring congestion situations.

Adler (1999) performed a laboratory experiment and determined that traveler information has significant short-term benefits to drivers unfamiliar with the network and that benefits decrease as familiarity increases. Hato, et al. (1999) found that reaction to traveler information is determined by an individual's driving experience, individual characteristics, and the scope of information provided. Table 2-5 summarizes the current simulation capabilities with regard to traveler information.

Table 2-5: Response to Traveler Information

Driver Response	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Route choice	8	4	8		4
Type of information					
Traveler information	9	3	9		3
Route guidance	8	4	8		4
Mean of obtaining information					
Broadcast	4	8	3	1	8
Location based	8	4	8		4
Individual	9	3	9		3

Eight of the systems model en-route driver response, with slightly different approaches. Generally, the systems have both traveler information and route guidance provided via both location based (i.e., VMS) as well as individual (i.e., on-board device) systems. However, not all of the systems explicitly distinguish between traveler information and route guidance, as the traveler information provided is a cost (travel time or another model-specific cost) used in the dynamic route choice model. Only three systems (Paramics, VISSIM and INTEGRATION) support broadcast traveler information, where drivers obtain information at a user-specified time interval.

One simulation system (AIMSUN) models dynamic driver response by associating specific actions with information for certain driver groups. For example, vehicles with a particular destination can consider changing paths when they receive information that explicitly affects them and their current route. The model contains a library, which can be modified by the user, of messages with corresponding actions.

One approach, where the route choice model uses real-time data rather than historical data if the vehicle passes a VMS or has an on-board device, is used with some variations in several systems. ARTEMIS distinguishes between unguided and guided vehicles in that the route choice of unguided vehicles is based on perceived minimum cost to destination while that for guided vehicles is based on the current, minimum cost to destination. A unique feature of ARTEMIS is that vehicles queuing for longer than a user-defined critical time, will seek a less congested path. In the same way, guided vehicles (with an on-board navigation system) and those vehicles that pass a VMS in MITSIMLab receive updated real-time link travel times that are then used in the route choice model. The fractions of guided and unguided vehicles are user-defined. VISSIM also updates travel times for vehicle classes that get en-route traveler information (either broadcast at pre-specified time intervals, at certain decision points, or, to equipped vehicles) but from the vehicles current position to the desired destination on all alternative routes that are used by other vehicles. Route guidance finds the optimal route from the current position to the desired destination based on these travel times and other user-defined cost values.

TransModeler explicitly models the difference between traveler information and route guidance. Traveler information simply provides updated link travel time values that may be used (depending on driver group specific parameters) as inputs into the route choice model to those who receive them via VMS or on-board devices. Route guidance information suggests or requires an action on the part of the driver (i.e., routing information or lane changes due to downstream lane closures). Drivers only process information that is relevant to them or on a potential path to their destination.

Paramics allows the user to create custom route choice systems through API. Though DRACULA does not have en-route guidance, it provides dynamic speed limit (i.e., school zones) information to vehicles with onboard devices. This information influences future path selection. Paths are selected daily and driver route choice is a function of the historical experience of the driver.

2.2.2 Traffic Control

Traffic control devices clearly impact driver behavior. The Highway Capacity Manual (HCM, 2000) distinguishes between traffic flow on freeway and signalized arterial streets. Not only do intersections reduce flow and cause delay, but traffic control devices result in significant acceleration/deceleration and lane changing for turning movements. For the traffic control to work effectively, it must be seen and understood. There have been numerous studies using driving simulators (Allen, 2004) to study the effect of visibility, location, and physical configuration of control devices on drivers understanding of their environment. Toll plazas are a unique form of traffic control device as they often occur on freeways. Not only do toll plazas result in higher trip cost and often in delay, but with the mix of electronic toll collection (ETC) and cash vehicles can result in uneven queues that block lanes, significant weaving and ultimately result in safety problems (Lieberman, et al., 2004). Table 2-6 summarizes the current simulation capabilities with regard to traffic control.

Traffic control devices and their control logic are represented in all of the models, and in most have a direct effect on driver acceleration. Visibility of the traffic control device is represented in most of the models and affects behavior in about half of the systems by influencing the point when drivers begin to respond to the signal or sign. The device size and display itself are only represented and affect behavior in AIMSUN and VISSIM. The physical location of the control device and associated stop lines are represented in the majority of the models, but attributes such as the height and position relative to the roadway do not play a role in any of the models.

Table 2-6: Traffic Control

Driver Response	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Device Property					
Type	12		10		2
Size and display	4	8	2		10
Visibility	10	2	10		2
Location	11	1			12
Control Logic					
Control logic type	12				12
Cycle length / green time	12				12
Electronic enforcement		12		3	9
Toll collection					
Technology type	8	4	7	1	4
Processing delay	6	6	5		7

The control logic behind these devices is also represented in all of the systems. Pre-timed, actuated and coordinated control logic exist in most models. The type of logic does not affect driver behavior in any of the models, and so, for example, drivers do not react differently to a green light in a pre-timed signal compared to an actuated signal or consider permitted/protected left turns at intersections when choosing routes.

None of the surveyed simulators represent surveillance in the form of electronic enforcement. However, Paramics, VISSIM and MITSIMLab can represent surveillance by proxy via changed speed distributions. In MITSIMLab the user also can adjust the percentage of drivers that would comply with the traffic light. Additionally, Paramics indicated that red-light enforcement could be simulated by decreasing the green time to mimic drivers stopping early when red-light cameras or police presence is known.

Toll collection was modeled in the majority of systems, with direct acceleration effects as vehicles slow or stop to the necessary speed. Route choice was also explicitly represented as an additionally cost and sometimes delay is associated with paths that include toll collection. Additionally, in several models the restriction of some toll lanes to drivers with smart tags was included. Lane changing and weaving are explicitly affected by toll plazas in many (AIMSUN, CubeDynasim, MITSIM, TransModeler, VISSIM and WATSIM) systems. Processing delay is incorporated into many models based on a distribution and vehicle classification (for example, average delay of those with smart tags would differ from those without).

2.2.3 Evaluation

Advanced Traveler Information Systems (ATIS) are emerging as important tools to alleviate traffic congestion through provision of real-time information to drivers. This is an area where detailed simulation systems are particularly useful, since the effects of ATIS technologies can only be captured and evaluated through modeling of the responses of individual drivers to the information. Table 2-7 presents the status of the best practices in modeling response to traveler information.

Table 2-7: Best Practices of Response to Traveler Information

Influencing Factor	Route Modification
Type of Information	∅
Traveler information	∅
Route guidance	∅
Means of obtaining information	
Broadcast	∅
Location based	∅
Individual	∅

A significant portion of the systems surveyed do not model en-route route choice at all. Most other systems do not differentiate between traveler information (general presentation of traffic conditions) and route guidance ("turn here" type instructions). Similarly, only some of the systems capture the differences between the various means of information such as VMS, broadcast and in-vehicle. With some variations, all existing systems capture the impact of traveler information by augmenting the travel times used in the route choice models with network-wide and detailed real-time information. These approaches fail to capture the effects of the different media. Travelers associate different levels of accuracy and reliability to different sources of information and, thus, their response to the different media varies. Also, different services may present information at different levels of detail. For example, a VMS can only display a few generic items of information, whereas an in-vehicle unit may provide customized, very detailed, information. As a result of the failure of existing systems to capture these aspects of traveler information, they, in many cases, can only be used to evaluate ATIS at a conceptual level under idealized conditions, but not at the detailed operational level required to fine-tune such technologies.

The simulation systems surveyed represent a wide variety of traffic control devices and the logic that controls them in great detail. This is not surprising given that many of the simulation applications center on evaluating various traffic control strategies. The main effect of control devices on driver behavior is captured through the guidance and information control they display (e.g. green or red light, various messages displayed on a VMS) and through their visibility to drivers. These factors are very well represented in existing systems.

Secondary effects may be seen in drivers' response to the underlying control logic and not only to the display. For example, drivers may react differently to a green light which is part of a green wave along an arterial compared to the case that isolated intersections are operated separately. Drivers also may be more likely to use the amber time to cross an intersection or run a red light when the signal cycle is longer. These effects are not represented in current systems. Similarly, control features, such as the physical location of light heads in terms of height and position relative to the roadway, that may be important if the simulation system is used to evaluate the detailed design of an intersection, also are not represented.

Table 2-8: Best Practices of Traffic Control

Influencing Factor	Acceleration	Lane Changing	Route Modification
Device properties	●	○	○
Control Strategy	○	○	○
Surveillance / Enforcement	∅	○	○
Toll collection	∅	∅	∅

2.3 Environment

2.3.1 Incidents

The primary traffic effect of incidents is lane closures or blockages, which result in reduced capacity and congestion. Lane closures require forced lane changes and the resulting congestion makes cooperative lane changing necessary. Most lane changing systems assume that vehicles may only change lanes if they do not interfere with vehicles in the destination lane by forcing them to slow or stop. In a congested situation, vehicles would not be able to change lanes without cooperation from vehicles in the destination lane (Hidas, 2002). Additionally, incidents increase travel time on the affected links, which may impact driver's route selection in the presence of information. Table 2-9 summarizes the current simulation capabilities with regard to incidents.

Table 2-9: Incidents

	Represented		Effect on behavior		
	Yes	No	Direct	Proxy	None
Incidents					
Inputs	11	1			
Influencing factor					
System effects					
Lane closures	11	1	11		1
Shoulder use/closure	3	9	2	3	7
Distractions	5	7		6	6
Behavioral effects					
Emergency braking	10	2	10		2
Rubber-necking	9	3	9		3

Eleven of the systems model incidents. All have inputs for the incident's location, lanes affected, start time and duration. However, they do not all include all of the system and behavioral effects related to incidents. Lane closures clearly affect acceleration and lane changing. For those systems that have dynamic route choice, lane closures also implicitly affect route choice if information is available as travel times are increased for links and paths with lane closures.

Only three systems explicitly capture shoulder usage or closure. However, the shoulder status only affects driving behavior in VISSIM and Paramics, where the effects are the same as those for a standard lane. Additionally, three systems capture the behavioral effects of shoulder status using a proxy by modifying the link maximum speed. The behavioral effects of distractions in terms of degrading effects on adjacent lanes and/or lanes in the opposite direction is modeled in five of the systems via slow speed zones or reducing the free-flow speed of affected links.

Almost all tools that model incidents capture emergency braking, which directly affects the acceleration of nearby vehicles and in some systems, lane changing. It also implicitly affects route choice by increasing link or path travel times in those systems with route guidance. Nine of the systems capture the effects of rubber-necking via slow speed zones, or reduced maximum speeds at the incident location, to adjacent and opposite direction lanes. Rubber-necking affects acceleration, car-following and implicitly route choice (in those systems that have route guidance) with increased link costs.

2.3.2 Work Zones

Work zones typically reduce the number of available lanes, which cause a reduction in capacity and can create congestion. As with incidents, this may require cooperative lane changes. Other features typical of work zones are narrower lanes, lack of shoulder, abrupt lane shifts and traffic control devices. These factors may cause drivers to be more cautious or drive less aggressively.

A recent study at the University of Illinois developed speed-flow curves for work zones based on the principle that drivers reduce their speed based on work zone operating factors such as work intensity, lane width and lateral clearance. Field data from the eleven interstate work zone sites in Illinois used for this study indicated speed reduction as well as larger headways for all traffic flow levels (Benekohal, et al., 2003). According to another study of speed-reduction patterns (Benekohal, et al., 1992), drivers tend to reduce their speeds at different locations within a work zone. While 63 percent of all drivers reduced their speeds after passing the first work zone sign, 11 percent reduced when they neared the location of construction activities and 11 percent did not reduce speed at all (the remaining did not indicate a pattern). Additionally, a study of traffic in interstate highway work zones revealed a safety paradox – vehicles traveling in work zones with higher speed limits demonstrated a significantly smaller time gap acceptance than those traveling within zones with slower speed limits (Sun and Benekohal, 2003).

Table 2-10 summarizes the current simulation capabilities with regard to work zones. As shown, none of the systems explicitly model work zones. Ten of the systems capture work zone effects by modeling it as a pre-defined incident. However, this approach does not necessarily capture all the system and behavioral effects associated with work zones.

Table 2-10: Work Zones

	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Work Zones					
Inputs	10	2			
Influencing factor					
System effects					
Variable/reduced speeds	10	2	10		2
Lateral clearance	4	8	1	4	7
Lane shifts	6	6	4	2	6
Lane width reductions	6	6	3	3	6
Reduced shoulder	5	7	1	4	7
Pavement markings	4	8	2	1	9
Behavioral effects					
Emergency braking	10	2	10		2
Rubber-necking	9	3	9		3
Visual distractions	5	7		6	6
Aural distractions	3	9		4	8

Reduced speeds and variable speed limits are represented in all of these systems; variable speed limits clearly affect driver acceleration, lane changing, and indirectly route choice for those with dynamic route guidance. Only a handful of systems capture other system effects related to work zones. AIMSUN captures the effects of lane shifts, lane width reductions and reduced shoulder through the link characteristics, which affects the car-following model and acceleration behavior. CubeDynasim explicitly represents lane shifts with a unique link type that affects lane changing. VISSIM explicitly addresses the issue of lateral clearance and reduced road width with a user-specified distribution of required clearance distance. Vehicles with a clearance distance smaller than the width of the road will undergo a forced lane change or select an alternate path.

MITSIMLab, Paramics and WATSIM modify the link characteristics by reducing free flow speeds to replicate the driving behavior resulting from these system effects. Additionally, in

Paramics, restrictions can be placed on each lane to prevent vehicles of certain widths from using them.

Emergency braking and rubber-necking are modeled as described in the section on incidents. None of the systems has explicit parameters to model visual and aural distractions. Several systems attempt to capture these effects by changing average link free-flow speed and with obstacles linked with a slow speed zone, respectively.

2.3.3 Weather

Inclement weather reduces visibility and traction of the road and undoubtedly affects driver behavior. While literature on the effects of weather on driver behavior is not abundant, several field studies correlating weather conditions or warnings of poor weather-related road conditions to driving behaviors have been conducted.

A study at the University of Virginia found traffic volume reductions ranging from four to 10 percent in light rain and 25 to 30 percent with heavy rain (Byrne, et al., 2003). The same study resulted in a 5-6.5% average decrease in vehicle speed, regardless of rain intensity. Several other studies have indicated that there are significant speed reductions on freeways during adverse weather conditions (typically ranging from 10-30 percent). For example, Knapp, et al. not only observed an average speed reduction, but also noted that off-peak speed reductions were highly correlated with visibility and surface conditions (Knapp, et al., 2001). Additionally, a University of Vermont study of traffic flow on signalized arterials concluded that inclement weather had a significant impact on the values of saturation headways and therefore, saturation flow rate (Agbolosu-Amison, et al., 2004). The study also noted that slushy and snowy conditions seemed to have the most impact on flow rate at signalized intersections. According to a Goodwin study, speed reductions on signalized arterial streets range from 10 to 25 percent on wet pavement and from 30 to 40 percent on slushy or snowy pavement while travel time delays can increase by 11 to 50 percent, depending on the severity of the weather (Goodwin, 2002). Another study reports average travel time delays of 14% for the Washington, D.C. metropolitan area (Stern, et al, 2003).

Not only does experiencing weather conditions affect driver behavior, but knowledge or warning of inclement weather also has been seen to result in more cautious driver behavior. A field study to test the effect of variable message signs that provided slippery road condition information found that drivers reduced speeds and increased headways. The warning also resulted in psychological effects of refocusing of attention to seek cues on potential hazards, testing the slipperiness of the road, and more careful passing behavior (Luoma, et al., 2000). Another field study in Britain resulted in similar findings – drivers understand the need to reduce speeds and increase headways in inclement weather conditions. However, in this study, drivers only reduced their average speed by 3 mph, not enough to make a significant difference in required braking distance or safety. Edwards proposed that these behaviors were a result of drivers over-estimating their driving capabilities, even while adapting to their environment (Edwards, 1999).

Table 2-11 below summarizes the current simulation capabilities with regard to weather.

Table 2-11: Weather

Influencing Factor	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Conditions					
Wind	4	8		5	7
Rain	6	6		7	5
Fog	6	6		7	5
Snow	6	6		7	5
Ice	6	6		7	5
Lighting	5	7		6	6
System Effects					
Reduced visibility					
Systemwide	6	6	4	3	5
Localized	7	5	4	4	4
Reduced surface quality					
Systemwide	7	5	3	5	4
Localized	6	6	2	5	5

As shown above, none of the systems explicitly model weather. Six systems (AIMSUN, DRACULA, Paramics, TransModeler, VISSIM, and WATSIM) represent weather conditions by proxy. AIMSUN, DRACULA, Paramics, and WATSIM change link characteristics of free-flow speed, speed limits, or capacity while TransModeler and VISSIM additionally vary driver/vehicle characteristics such as the desired speed curve or acceleration capabilities.

Several systems contain parameters that represent the system effects of weather conditions, including visibility (CORSIM, DRACULA, MITSIMLab, TransModeler and VISSIM) and surface quality (CORSIM, MITSIMLab and VISSIM), which affects acceleration and lane changing. Other systems represent the effects by proxy through changing link characteristics.

2.3.4 Evaluation

Environmental elements are important factors affecting driver behavior. Table 2-12 represents the current best practices of modeling these important environmental factors.

Table 2-12: Best Practices of Important Environmental Effects

Influencing Factor	Acceleration	Lane Changing	Route Modification
Conditions			
Wind	∅	○	○
Rain	∅	○	○
Fog	∅	○	○
Snow	∅	○	○
Ice	∅	○	○
Lighting	∅	○	○
System effects			
Lane closures	○	●	∅
Shoulder use/closure	∅	○	
Reduced speeds	∅		
Lateral clearance		●	
Lane shifts	∅	○	
Pavement markings	∅	○	
Reduced visibility	∅	○	○
Reduced surface quality	∅	○	○
Behavioral effects			
Distractions	∅	○	
Emergency braking	●		
Rubber-necking	∅		

Most systems capture the impacts of incidents and work zones in similar ways. Blocked lanes cause drivers to change lanes. Vehicles in other lanes may be forced to slow down by modifying the definitions of maximum and desired speeds in the same ways these mechanisms were used to model the impacts of the geometric design. The same criticism we discussed in that section also applies: maximum and desired speeds mostly affect the acceleration of drivers in uncongested conditions and have much less impact on accelerations in congested conditions and on lane changing behaviors. Moreover, this approach also implicitly assumes that apart from blocked lanes and their effect on desired speeds, incident locations and work zones are no different from normal sections since the same behavioral models with the same parameter values still apply. That is, if the geometry is similar (e.g., the number of blocked and open lanes), drivers' behavior and the resulting traffic conditions around an incident, a work zone and "standard" facilities such as a lane-drop would also be similar. Unfortunately, empirical evidence to support or disprove this assumption is scarce.

This kind of assumption is clearly invalid for modeling weather effects. Adverse weather conditions result in defensive driving behavior. This manifests itself in reduced desired speeds and more conservative car-following and lane-changing behaviors. However, similar to the cases of incidents and work zones, as well as geometry effects, the only mechanisms available to users to capture weather effects are the maximum and desired speed, and acceleration capabilities.

2.4 Vehicle Characteristics and Type

2.4.1 Vehicle Characteristics

Vehicle characteristics clearly play a large role in influencing driver behavior. Some, such as acceleration and speed capabilities, are quite straightforward. Vehicle dimensions also affect driver behavior: length affects gap acceptance while changing lanes; height affects visibility, or lack thereof; width affects speed and blocks neighboring lanes; and vehicle mass affects acceleration. Additionally, turning radii affects maneuverability. Table 2-13 summarizes the current simulation capabilities with regard to vehicle characteristics.

In all systems, length is a major factor in lane-changing and acceleration due to gap acceptance dependence on vehicle length. Width is modeled in seven of the systems, and height to a lesser extent in only four systems. MITSIMLab allows the user to input different turning restrictions (based on vehicle type) to capture situations where the vehicle is too large to reasonably complete the maneuver (due to tunnels or overpasses). Vehicle width only affects behavior in VISSIM, where vehicle clearance is required and affects acceleration (vehicles will slow if the lane is not wide enough for them), lane changing (vehicles will move to alternate lanes if possible), and route choice (drivers may select an alternative route with wider lanes). Vehicle height only affects behavior in MITSIMLab, where the user can specify height restrictions on the link so specific vehicles may not select a path using that link.

Table 2-13: Vehicle Characteristics

Influencing Factor	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Vehicle dimensions					
Width	7	5	1		11
Length	12		11		1
Height	4	8	1		11
Articulated vehicle section	6	6	1		11
Vehicle mass	4	8	4		8
Passenger capacity	8	4			12
Acceleration capability	12		12		
Speed capabilities	12		12		
Turning radii	1	11	1		11

While six systems represent articulated vehicles, the only model in which it affects driver behavior is TransModeler (affects lane-changing). Only INTEGRATION, Paramics, TransModeler and VISSIM contain parameters for vehicle mass, which directly affect acceleration (and emissions modeling in VISSIM). Eight systems represent passenger capacity, but it does not affect driver behavior in any of them.

All systems contain parameters for acceleration and deceleration capabilities and speed capabilities, which directly affect acceleration and in some cases lane-changing. VISSIM also contains explicit parameters for turning radii, which affects acceleration and route choice (the vehicle will not complete a turn if it is physically unable to, in which case it may need to select an alternative route).

2.4.2 Vehicle Types

While only limited literature exists on this topic, there is little doubt that drivers interact differently with various vehicle types. For example, drivers tend to avoid driving in close proximity or behind large trucks and act more cautiously near motorcycles and bicycles. Large trucks not only have more restricted acceleration and deceleration capabilities, but they also limit visibility downstream, often block signs (Abramson, 1971) and create a draft and more spray in wet road conditions. Motorcycles cause different driver behaviors because they are more difficult to see, can share lanes with other vehicles and are not as protected (perhaps causing people to drive more cautiously). Additionally, drivers tend to avoid following buses due to their slow speeds and frequent stops (Silva, 2001). Pedestrian interaction and interference also are significant, along with interaction with on-street parking maneuvers, particularly in large, dense urban networks. Table 2-14 below summarizes the current simulation capabilities with regard to modeling vehicle types.

Most systems define several vehicle types with specific characteristics (or distribution of characteristics) to distinguish their driving behavior. With this flexibility a variety of passenger, commercial, and transit vehicles can be modeled depending on the mix of vehicles using the network. These vehicle types are fairly standard across the systems and have pre-defined and user-defined parameters. However, emergency vehicles, motorcycles, bicycles, and pedestrians are not widely modeled. Of the systems representing emergency vehicles, VISSIM is the only one that allows emergency vehicles to run red-lights. CORSIM now includes an experimental component that allows other vehicles to react to the emergency vehicle (McHale and Holm, 2003). VISSIM is also the only simulation system reviewed that allows motorcycles and bicycles to pass other vehicles in the same lane.

Interactions among the different vehicle types are not widely modeled. Most simulation tools base their car following systems on the driving characteristics of surrounding vehicles. In MITSIMLab, the behavior of vehicles following trucks and of trucks themselves is different. TransModeler has explicit parameters relating to large trucks and heavy equipment in their lane changing and acceleration systems.

Table 2-14: Vehicle Type

Vehicle Type	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Passenger vehicles					
Automobiles	12				12
Guided vehicles	7	5			12
SUVs	11	1			12
Taxis	9	3			12
Motorcycles	6	6			12
Commercial vehicles					
Emergency vehicles	6	6			12
Large trucks	12		1		11
Heavy equipment	7	5	1		11
Small trucks/vans	12				12
Transit vehicles					
Buses	12				12
Minibuses	11	1			12
Trains	8	4			12
Light rail/trams	9	3			12
Non-motorized vehicles					
Bicycles	4	8			12
Pedestrians	6	6	5		7

2.4.3 Evaluation

The characteristics of the vehicle and the interactions between different vehicle types play an important role in driving behavior. The vehicle dimensions affect its maneuverability, and, therefore, impact both acceleration and lane-changing behaviors. Vehicle capabilities in terms of speed, acceleration and turning radii act as constraints, which dictate what the driver can and cannot do. As shown in Table 2-15, most of these factors, and in particular the vehicle length and maximum capabilities seem to be adequately represented in most simulation systems.

Table 2-15: Best Practices of Vehicles Characteristics and Interactions

Influencing Factor	Acceleration	Lane Changing	Route Modification
Width	●	●	●
Length	●	●	●
Height	●	●	●
Articulated vehicle section	○	∅	
Vehicle mass	●		
Acceleration capability	●		
Speed capabilities	●		
Turning radii	∅		●
Passenger vehicles	○	○	
Commercial vehicles	∅	∅	
Transit vehicles	○	○	
Non-motorized vehicles	○	○	

The situation is different in representing vehicle types. Most systems allow great flexibility in defining and modeling a large number of vehicle types. In most cases, however these vehicles types and their characteristics are not taken into account when vehicles interact with each other. For example, a vehicle would follow another vehicle in the same way regardless of the type of the lead vehicle. However, there is empirical evidence that this is not true in reality. Drivers would follow trucks, buses and even SUVs that obscure their field of view differently than they would passenger cars (Yoo and Green, 1999). Similarly, the behaviors of buses in service and the vehicles surrounding them may be affected. For example, bus drivers who are required to make stops, would change lanes differently than other vehicles. The drivers of other vehicles would be more likely to change lanes when they follow a bus in service to avoid being forced to stop (Silva, 2001)

2.5 Traveler Characteristics

2.5.1 Assessment

The National Highway Traffic Safety Administration (NHTSA) estimates that driver inattention is a factor in 25 to 30 percent of traffic crashes in the United States (Shelton, 2001). With drivers engaged in distracting activities – including eating and drinking, manipulating music, grooming, conversing, using cellular phones, and reading, among others – 16 percent of the time their vehicles are moving (Stutts and Hunter, 2003), it is easy to see that distraction and inattentiveness are significant factors affecting driver behavior. According to a study by the American Automobile Association Foundation for Traffic Safety, drivers are more often preoccupied with music, food, grooming, and reading than cell phone usage (Crawley, 2003). Ninety-one percent of drivers engaged in manipulating audio controls, 71 percent ate or drank, 46 percent groomed, and 40 percent read (though most when the vehicle was stopped), while fewer than 35 percent used cellular phones (Stutts and Hunter, 2003). The perception and reaction times of distracted drivers increase, which leads to delayed acceleration and braking and potentially hazardous lane-changing maneuvers, affecting the acceleration behaviors of nearby vehicles.

Because humans are complex, so is their driving behavior – occurring simultaneously within three conscious behavioral areas of the individual: affective, cognitive, and sensorimotor (James, 1984). A study of driver psychology found the driver to be involved in the effort to comply to rules, norms, and roles of driving behavior, which involves the driver’s motivation, character, and conscience, as well as their rationality, understanding and driving efficiency and sensory awareness. All of these psychological characteristics affect driving behavior and make it difficult to model.

While it has been argued that driver attitude or motivations are uncorrelated with observable dynamic behavior, it is hard to believe that driver psychological factors do not influence at least their acceleration behavior. Winsum (1999) argues that drivers aim to maintain a following distance based on a time headway, which, while primarily dependent on driver skills, also depends on driver state, visual conditions, and the mental effort and attention the driver is willing to pay to the lead vehicle. In the context of car-following behavior, Boer (2000) argues that psychological elements must be included in the systems. Drivers perform many tasks while driving (necessary tasks like shifting as well as extraneous tasks causing distractions), so car following receives sporadic attention and control. In addition, drivers are satisfied with a range of conditions rather than one optimal condition, and drivers use a set of highly informative perceptual variables to guide decision-making and control. Table 2-16 summarizes the current simulation capabilities with regard to traveler characteristics.

Driver perception is only represented in TransModeler and VISSIM. TransModeler models perception in the form of driver response time, which affects acceleration (different desired acceleration rates based on driver type) and lane-changing (different desired speed and minimum gap acceptance). VISSIM models a perception threshold, which affects acceleration, lane-changing and route choice. CubeDynasim uses visualization zones to simulate driver visual acuity.

Nine of the systems model familiarity of drivers with the network, which affects driver route choice. Additionally, in AIMSUN, CORSIM, MITSIMLab and TransModeler it also affects lane changing by increasing the visibility of traffic control devices. All systems represent driver aggressiveness, which affects desired acceleration and minimum gap acceptance in lane-changing. Six simulation tools model driver value of time, which affects route choice in all systems, and the level of aggressiveness in some.

Table 2-16: Traveler Characteristics

Influencing Factor	Represented		Effect on Behavior		
	Yes	No	Direct	Proxy	None
Perception					
Visual acuity of drivers	2	10	2	1	9
Attentiveness of drivers	2	10	2		10
Decision-making					
Familiarity of drivers with network	9	3	9		3
Driver aggressiveness	12		12		
Driver value of time	6	6	6		6
Compliance					
Speed limits	9	3	9		3
Traffic signals	9	3	8		4
Ramp Metering	7	5	6		6
Lane restrictions/usage	9	3	8		4
Route guidance	8	4	7		5
Road type preference	5	7	5		7
Control					
Driving skill	2	10	1	1	10
Driver impairment	1	11	1		11

For those systems that consider compliance to traffic signals and signs, acceleration behavior is affected. Lane restriction compliance affects acceleration and lane-changing behaviors, and in some cases, route choice. CubeDynasim contains a violator vehicle type for speed limit and traffic control compliance. Similarly, VISSIM specifies traffic control compliance by vehicle class but utilizes a desired speed curve distribution for speed limit compliance. Route guidance compliance clearly affects route choice, as does road type preference.

Driver control is only represented in VISSIM, similarly to the perception threshold that is defined by driver type. It affects both acceleration and lane-changing. WATSIM represents driving skill though a proxy using a driver characteristic ranging from aggressive to cautious.

2.5.2 Evaluation

Every decision that humans make is influenced by the characteristics of the decision-maker. Driving and travel behaviors are no different. Table 2-17 presents the best practices of modeling traveler characteristics.

Table 2-17: Best Practices of Important Traveler Characteristics

Influencing Factor	Acceleration	Lane Changing	Route Modification
Driver network familiarity		●	●
Driver aggressiveness	●	●	
Driver value of time		●	●
Compliance	●	●	
Control	∅	∅	

The heterogeneity that driver characteristics bring about has an important effect on traffic. However, it is not critical, in most traffic simulation applications, to identify the precise psychological sources of that heterogeneity. The approach taken by most systems is to represent driver heterogeneity by one or a few factors (often dubbed "aggressiveness" or similar terms) that affect acceleration, lane changing and route choice behaviors. Most systems also include factors that are more narrowly defined, such as familiarity and compliance, to address the variability in specific situations. While this approach seems appropriate for the level of detail required in most applications, a clear methodology for determining appropriate psychological representations remains an open question. The psychological factors represented by the driver characteristics variables are unobservable and so, the distributions of these factors can only be identified through the use of sophisticated formulation and estimation techniques of the various behavior systems.

2.6 Summary and Conclusions

This section summarizes findings with respect to state-of-the-practice in representing the influencing factors in microscopic traffic simulation models and the gaps that have been identified.

Lane changing and acceleration behaviors are affected most by those factors that capture the impact of the geometric design, incidents and work zones and the effects of weather conditions. The treatment of these factors in traffic simulation models is very limited and basic. In most cases, their effects are captured by proxy mechanisms that allow the user to modify the distributions of maximum speeds and desired speeds. This approach is limited in that it only addresses situations in which maximum and desired speeds are significant factors, namely acceleration behaviors in uncongested traffic conditions. It does not capture the effects on lane-changing and acceleration in congested conditions, where maximum and desired speeds are of marginal importance. Even for these mechanisms that exist in traffic simulation models, there are very few empirical results in the literature to guide the user in setting up and changing the values of the relevant parameters to quantify the effect of various factors. For example, rubbernecking, the phenomenon of vehicles (even in the unaffected opposite direction) slowing down near an incident is well recognized. It is a significant source of delays caused by incidents and its impact continues even after the physical blockage of the road is removed. Rubbernecking is often modeled by locally reducing the maximum or desired speed. However, in order to model it realistically there is a need to develop guidelines as to the extent of this reduction and the contributing factors (characteristics of the incident).

Information and the response to information directly affect route choice behavior. Existing models modify the travel times that factor into the route choice as the basic mechanism to incorporate the impact of traveler information. While this approach is reasonable, further work needs to be done to model the finer details of the information and the response to it, such as the differences between various means of providing information in terms of level of detail and perceived reliability. However, response to information is only one aspect that needs to be incorporated in route choice models. Many of the factors which were discussed above in the context of acceleration and lane-changing may also affect route choice. For example, drivers may show preference to particular facility types over others (e.g. highways over urban streets), pavement conditions and the geometric features of different routes may affect route choices in adverse weather conditions, etc. These considerations are largely ignored in most route choice models, which are primarily based on travel times.

Both driving behaviors (acceleration and lane-changing) and route choices are influenced by the driver and vehicle characteristics. These factors are important in that they reflect the heterogeneity in the population of drivers, which has a significant effect on traffic conditions. However, these factors are not observable. Nevertheless, they should be incorporated in behavior models as latent variables and their distributions in the population be estimated jointly with the other parameters of the various models. Once these distributions are estimated, the framework of most existing simulation models offers the capability to use these as inputs.

Chapter 3

Methodology

Chapter 2 reviewed the current state of the practice in traffic microsimulation capabilities to capture the impact of external factors. This chapter presents a framework for incorporating influencing factors in driving behavior models.

3.1 Framework

Generally, calibration and validation of microscopic traffic simulation models consists of two steps, as shown in Figure 3-1. First, the individual models that comprise the simulation are estimated using disaggregate data, independent of the overall simulation model. Next, aggregate data (traffic counts, speeds, occupancy) is used to fine-tune parameters and calibrate general parameters for the simulator. This approach was developed by Toledo, et al (2004) and has been applied in several cases studies.

The disaggregate data used in the first step includes detailed driver behavior information, such as vehicle trajectories of the subject and surrounding vehicles. Disaggregate data is complex, difficult to process, expensive and has several limitations. Because trajectory data, detailed, sub-second vehicle position data, is costly to obtain and analysis is quite laborious, it is generally limited to small sections of roadway in optimal conditions. This means that the data is not necessarily representative of not only each segment of the original study area, but also other locations. For this reason, the second step of the calibration framework is completed to refine the models.

More importantly for the purposes of this research, the limitations and expense of trajectory data mean that it is not available, specifically for many of the influencing factors of interest. For example, inclement weather conflicts with visibility conditions necessary for collecting the data. Incidents are difficult to record in that their location is unknown ahead of time and often their impacts are more widespread, for example with queue propagation, than the small study area. Geometric impacts can also make exacerbate the complexity and cost of trajectory data collection with difficult sight lines.

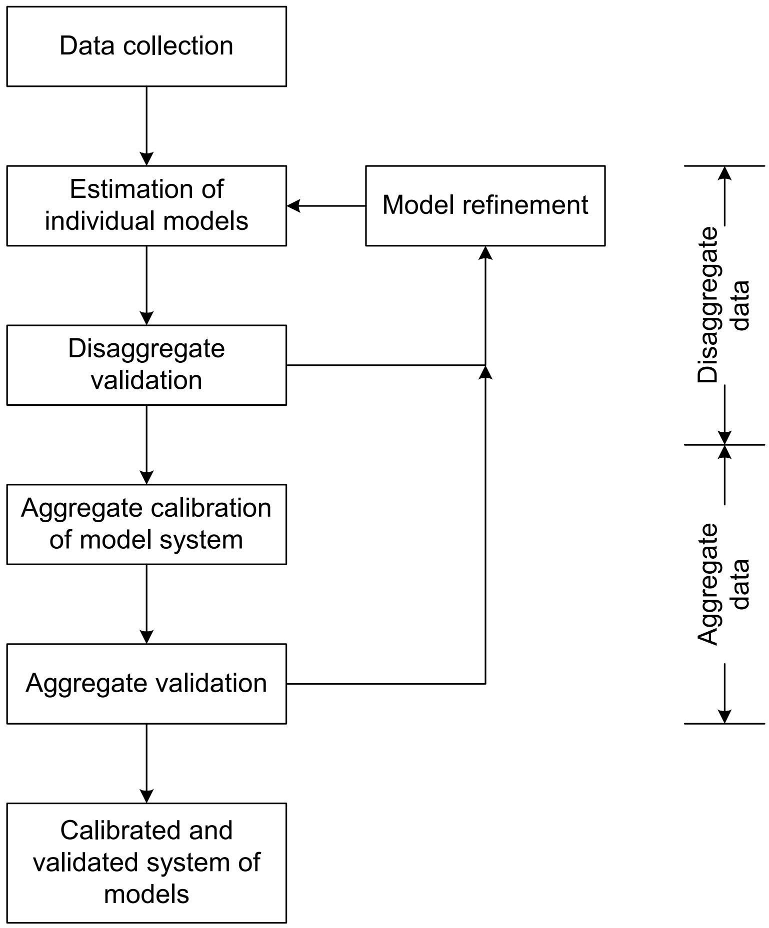

Figure 3-1: Overall Calibration Framework

3.2 Aggregate Calibration Methodology

Aggregate calibration is based on a formulation of an optimization problem that seeks to minimize a measure of the deviation between observed and corresponding simulated measurements. The reason for this approach is that, in general, it is not feasible to isolate the contribution of individual models to the overall error. For example, OD estimation methods require an assignment matrix as input. The assignment matrix maps OD flows to traffic counts at sensor locations. Usually the assignment matrix is not readily available and needs to be generated from the simulator. Therefore, the assignment matrix is a function of the route choice and driving behavior models used. Simulated flows are a function of the OD flows, driving behavior and the route choice model itself.

Hence, the following optimization problem, which simultaneously calibrates the parameters of interest (OD flows, route choice and driving behaviors) may be formulated:

$$\begin{aligned}
&\min_{\beta,\theta,OD} \quad f\left(M^{obs}, M^{sim}\right) \\
&s.t. \qquad M^{sim} = g\left(\beta,\theta,OD\right) \qquad\qquad (3\text{-}1) \\
&\qquad\qquad OD = \arg\min_{X} \left\| AX - Y^{obs} \right\|
\end{aligned}$$

where, β, θ and OD are the vectors of parameters to be calibrated: driving behavior, route choice and OD flows, respectively; M^{obs} and M^{sim} are vectors of observed and simulated traffic measurements, respectively; g(.) represents the simulation process; Y^{obs} are observed traffic counts at sensor locations; and A is the assignment matrix.

The problem above is very difficult to solve exactly. The OD constraint, for example, is a fixed-point problem, which is a hard problem in its own merit. Therefore, the iterative heuristic approach outlined in Figure 3-2, which accounts for interactions between driving behavior, OD flows and route choice behavior by iteratively calibrating driving behavior parameters and travel behavior elements, is used.

At each step, the corresponding set of parameters is calibrated, while the other parameters remain fixed to their previous values. The proposed calibration process proceeds as follows:

1. Initialize parameters β_0, θ_0 and OD_0.
2. Estimate OD and calibrate route choice parameters assuming fixed driving behavior parameters.
3. Calibrate driving behavior parameters assuming the OD matrix and route choice parameters estimated in step 2.
4. Update habitual travel times using the OD matrix, route choice and driving behavior parameters estimated in steps 2 and 3.
5. Check for convergence: if convergence, terminate.

   Else, continue to step 2.

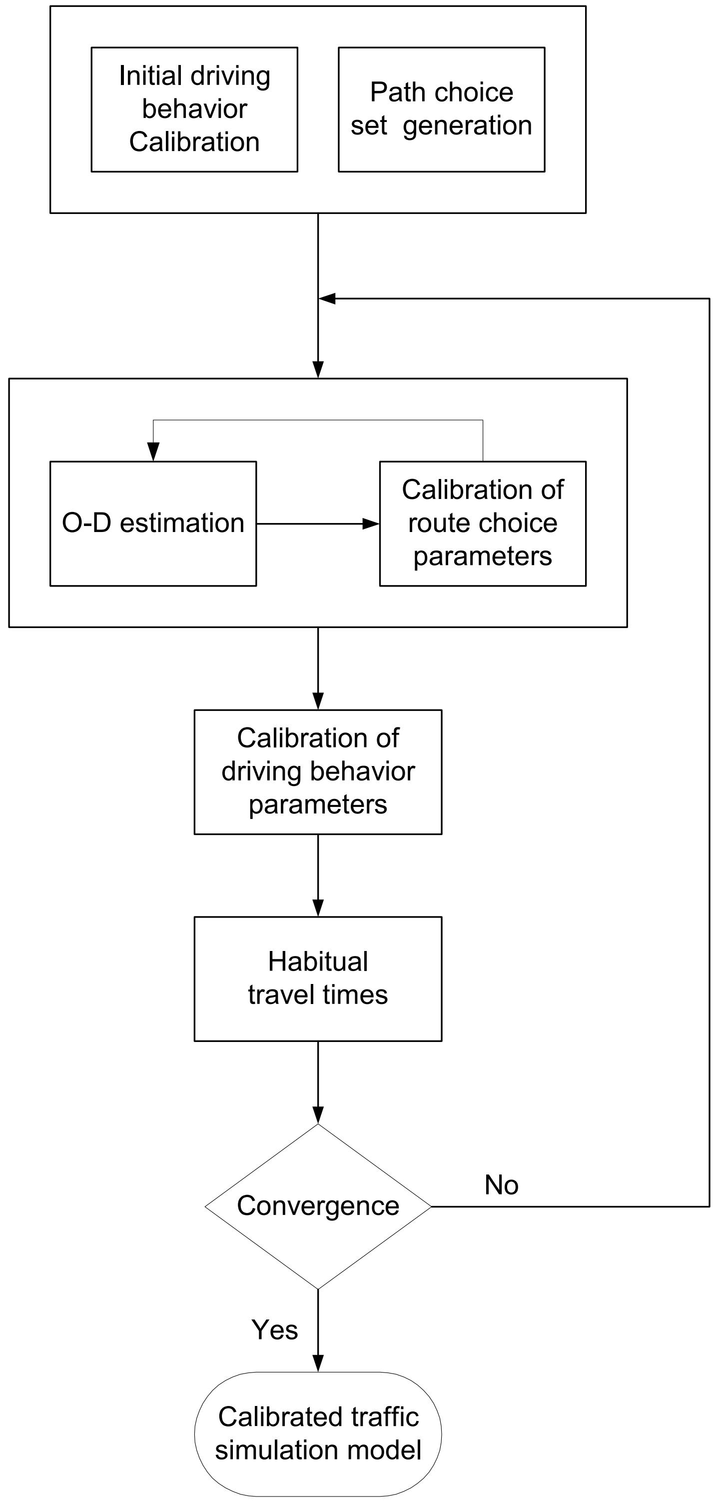

Figure 3-2: Methodology for Aggregate Calibration of Microsimulation Models

The following sections describe OD estimation and calibration of driving behavior parameters in more detail.

3.2.1 OD Estimation

The OD estimation problem is often formulated as a generalized least squares (GLS) problem. The GLS formulation minimizes the deviations between estimated and observed sensor counts while also minimizing the deviation between the estimated OD flows and seed OD flows. The corresponding optimization problem is:

$$\min_{x \geq 0} \left(AX - Y^H\right)^T W^{-1} \left(AX - Y^H\right) + \left(X - X^H\right)^T V^{-1} \left(X - X^H\right) \quad (3\text{-}2)$$

X and X^H are vectors of estimated and historical (seed) OD flows, respectively. Y^H are the historical (observed) sensor counts. W and V are the variance-covariance matrices of the sensor counts and OD flows, respectively.

However, in most cases the assignment matrix is not known. Therefore, the iterative process shown in Figure 3-3 is used: First, the simulation is run, using the calibrated parameters and a set of seed OD flows to generate an assignment matrix. This assignment matrix is in turn used for OD estimation. Due to congestion effects, the assignment matrix generated from the seed OD may be inconsistent with the estimated OD and further iterations are performed.

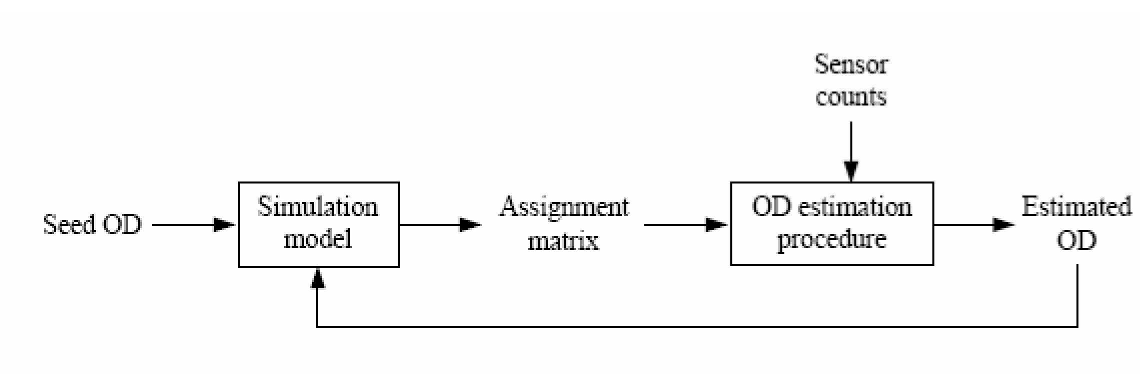

Figure 3-3: OD Estimation Process

3.2.2 Calibration of driving behavior parameters

Driving behavior parameters are calibrated by minimizing a function of the deviations of simulated measurements from observed ones:

$$\min_{\beta} \sum_{t=1}^{T} \sum_{n=1}^{N} \left(Y_{nt}^{sim} - Y_{nt}^{obs}\right)^2 \quad (3\text{-}3)$$

where, Y_{nt}^{obs} and Y_{nt}^{sim} are the observed and simulated speeds and/or flows, respectively, measured at sensor n during time period t. N and T are the number of sensors and time periods, respectively, and β are the parameters to be calibrated.

While the initial estimation (Ahmed, 1999) of driving models included a wide range of parameters, during this step only a limited set of parameters may be calibrated. Hence, given OD flows and steady-state travel times, a subset of driving behavior parameters is calibrated using the formulation shown in Figure 3-4.

To calibrate the parameters, the algorithm proceeds as follows: an original set of K points is generated consisting of a feasible starting point (specified by the user) and K-1 additional points generated from random numbers that satisfy explicit and implicit constraints. The objective function is evaluated at each point and the point having the highest function value is replaced by a point (satisfying constraints) which is located between the centroid of the remaining points and the rejected point. The process continues until the objective function value converges to the minimum.

The module accepts as input the measured flows, speed etc. values from sensors in the real network. Each time the objective function is evaluated, the simulator is called and the outputs from the simulator are used in the objective function. To take care of the stochasticity related to the simulator, the simulator can be run for a number of times and then the average value of the objective function over these runs can be used in the box algorithm.

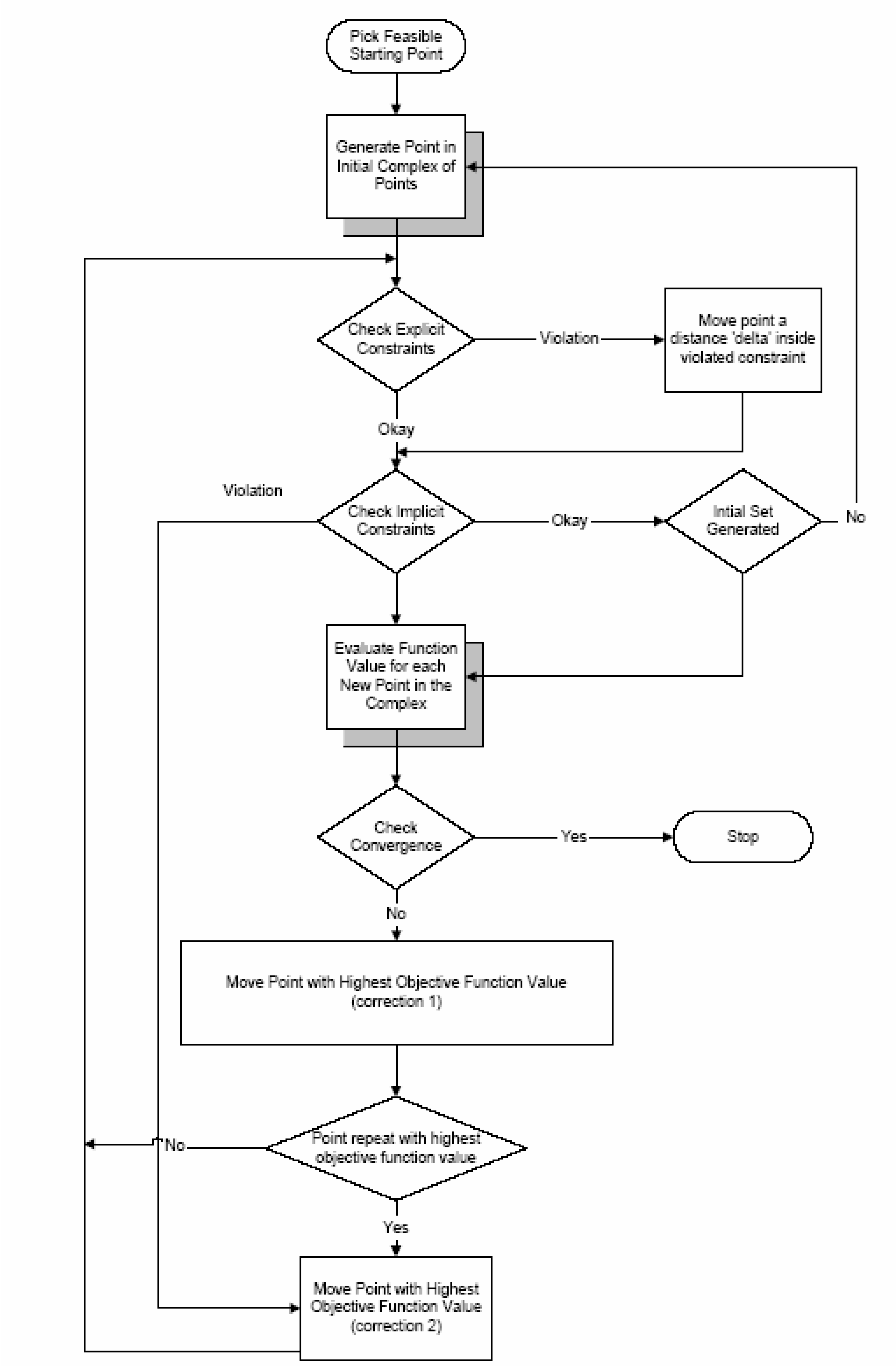

Figure 3-4: Box Algorithm used in Parameter Estimation

3.2.3 Validation Methodology

The purpose of validation is to determine the extent to which the simulation model replicates the real system. This is done by comparing measures of performance (MOPs), or statistics of outputs of interest from the two systems. There are several goodness-of-fit measurements that can be used to quantify the similarity between observed and simulated MOPs. The following is adapted from Pindyck and Rubinfield (1997).

The root mean square error (RMSE) and the root mean square percent error (RMSPE) quantify the overall error of the simulator, penalizing large errors at a higher rate than smaller ones. RMSPE quantifies the total percentage error and similarly, root mean normalized error quantifies the total percentage error using the average of observed records.

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^{sim} - Y_n^{obs}\right)^2} \quad (3\text{-}4)$$

$$RMSPE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\frac{Y_n^{sim} - Y_n^{obs}}{Y_n^{obs}}\right)^2} \quad (3\text{-}5)$$

$$RMSNE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\frac{Y_n^{sim} - Y_n^{obs}}{\bar{Y}^{obs}}\right)^2} \quad (3\text{-}6)$$

where, Y_n^{obs} and Y_n^{sim} are observed and simulated measurements at space-time point n, respectively.

The mean error (ME) and mean percent error (MPE) indicate the existence of systematic under-or over- prediction in the simulated measurements, and are calculated by:

$$ME = \frac{1}{N}\sum_{n=1}^{N}\left(Y_n^{sim} - Y_n^{obs}\right) \quad (3\text{-}7)$$

$$MPE = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{Y_n^{sim} - Y_n^{obs}}{Y_n^{obs}}\right) \quad (3\text{-}8)$$

Theil’s inequality coefficient, shown below, also provides information on the relative error.

$$U = \frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^{sim} - Y_n^{obs}\right)^2}}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^{sim}\right)^2} + \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^{obs}\right)^2}} \quad (3\text{-}9)$$

where U is bounded, $0 \leq U \leq 1$ and U=0 implies a perfect fit between observed and simulated measurements and U=1 implies the worst possible fit. This measurement may be decomposed into three proportions of inequality: bias (U^M), variance (U^S) and covariance (U^C), given by:

$$U^M = \frac{\left(\overline{Y}^{sim} - \overline{Y}^{obs}\right)^2}{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^{sim} - Y_n^{obs}\right)^2} \quad (3\text{-}10)$$

$$U^S = \frac{\left(\sigma^{sim} - \sigma^{obs}\right)^2}{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^{sim} - Y_n^{obs}\right)^2} \quad (3\text{-}11)$$

$$U^C = \frac{2(1-\rho)\sigma^{sim}\sigma^{obs}}{\frac{1}{N}\sum_{n=1}^{N}\left(Y_n^{sim} - Y_n^{obs}\right)^2} \quad (3\text{-}12)$$

where $\overline{Y}$, σ and are the means and standard deviations of the series and ρ is their correlation coefficient. $U^M + U^S + U^C = 1$, by definition. The bias reflects the systematic error while the variance proportion indicates how well the simulation model replicates the variability in the observed data. Both should be as close to zero as possible, and as a correspondingly, covariance should be close to 1.

3.3 Application of Aggregate Calibration

This thesis hypothesizes that some of the critical influencing factors discussed in the previous chapter can be captured and applied in existing driving behavior models with aggregate calibration and validation. Disaggregate data necessary to estimate driving behavior models that incorporate key influencing factors may not be available or technically possible to obtain. There also may be cases where the nature of the key influencing factor does not warrant the expense and labor involved in estimating the entire behavioral model. For example, weather is certainly a critical factor in determining driver behavior, but its impacts can perhaps be captured in the finetuning of parameters used with existing models rather than require an entirely new model structure.

The next chapter describes a case study and the simulation environment in which this approach will be applied and tested, as well as a description of the specific driving behavior models.

Chapter 4

Case Study

This chapter presents the case study, MITSIMLab, the traffic simulation laboratory utilized in this research, and existing driving behavior models that will be enhanced with the aggregate calibration methodology.

4.1 Case Study Description

For this thesis, the external effect of weather on acceleration and lane changing behavior is applied to a freeway corridor in Hampton Roads, Virginia. Figure 4-1 presents a map of the study area region.

Figure 4-1: Map of Hampton Roads Region

Weather is an exemplary influencing factor to test with this model. Literature found weather to be one of the most important causes of congestion and incidents. Adverse weather conditions, with precipitation and decreased visibility, are not suited well for disaggregate model estimation as trajectory data in these conditions is not available or very limited. Therefore, aggregate weather and traffic data can be used to fine tune the existing behavior models used in the microscopic traffic simulation that have been calibrated previously with disaggregate data.

A 3.6 mile section of I-264 eastbound, between mile markers 15.1 and 18.7, was used to test the approach. The section contains 3 on-ramps and 4 exits, including exits 16, 17a, 17b and 18. Figure 4-2 shows an aerial photo of the study corridor, with the exit 17 cloverleaf quite prominent and Table 4-1 identifies the exit destinations.

Figure 4-2: Aerial photograph of study corridor

Table 4-1: I-264 exit locations

Exit No.	Intersects	City/County
16	Witchduck Rd. - Route 190	Virginia Beach
17	Independence Blvd. - Route 225 (NB)/Route 410 (SB)	Virginia Beach
18	Rosemont Rd. - Route 411	Virginia Beach

Data was gathered from ADMS Virginia Smart Travel Lab and consists of sensor data (counts, occupancy and speed) as well as hourly weather data (precipitation, visibility and temperature) from the Norfolk International Airport weather station. Incident data was reviewed; however specific information regarding incident location was unavailable, and therefore eliminated from the study.

Two time periods – AM peak and PM peak – were used to calibrate the model. The hours between 6:00 - 7:00 AM and 4:00 - 5:00 PM were selected for the AM and PM peak, respectively. Fifteen days for each period, all without reported incidents, were used with a mix of days with precipitation, low visibility and fine weather days (high visibility and no precipitation). The PM period had significantly higher traffic volumes and densities, indicating congestion.

Maximum free flow speeds in the study area were reported as 65 mph, with recorded speeds ranging from 11 mph to 65 mph during the observed periods. The average speed on the mainline was 58 mph, ranging from 31 to 65 while densities ranged from 7 vpm to 66 vpm. The average flow was approximately 5900 vph. Precipitation for the observation periods ranged from none to 0.12 in/hr and visibility ranged from 0.13 miles to 10 miles (maximum reported visibility).

The following sections introduce MITSIMLab, the simulation environment utilized in this study, describe relevant driving behavior models and discuss preliminary data analysis.

4.2 MITSIMLab

MITSIMLab is a microscopic traffic simulation laboratory developed for the design and evaluation of Advanced Traffic Management Systems (ATMS) and Advanced Traveler Information Systems (ATIS). MITSIMLab can represent a wide range of traffic management system designs and model the response of drivers to real-time traffic information and control, thus simulating the dynamic interaction between the traffic management system and the drivers. MITSIMLab consists of three modules:

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

MITSIM represents the “real-world” with detailed traffic and network elements and their behaviors and is the focus of this thesis. 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 and along with 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 (desired speed and aggressiveness, for example) and vehicle characteristics and moves through the network according to acceleration (car-following) and lane-changing models. The acceleration model captures the response of a driver to conditions ahead as a function of relative speed, headway and other traffic measures. The lane changing model distinguishes between mandatory and discretionary lane changes. The driving behavior models implemented in MITSIM are discussed in more detail in the following section.

The TMS represents the traffic control and routing logic in the network under evaluation. The control and routing strategies generated by the traffic management module determine the status of the traffic control and route guidance devices. Drivers respond to the various traffic controls and guidance while interacting with each other. An extensive GUI is used for both debugging purposes and demonstration of traffic impacts through vehicle animation.

4.3 Driving Behavior Models

The driving behavior models implemented in MITSIM and described in detail below were estimated by Kazi Ahmed in his dissertation entitled *Modeling Drivers' Acceleration and Lane Changing Behavior* (1999). The integrated lane changing model was estimated by Tomer Toledo in his dissertation entitled *Integrated Driver Behavior Modeling* (2003).

4.3.1 Acceleration

MITSIM considers two acceleration regimes: free-flow and car-following. The free flow-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 is shown in Equation 4-1:

$$a_n^{ff}(t) = \lambda^{ff} \cdot \left[V_n^*\left(t-\tau_n\right) - V_n\left(t-\tau_n\right)\right] + \varepsilon_n^{ff}(t) \quad (4\text{-}1)$$

where,

$$\begin{aligned}
\lambda^{ff} &= \textit{constant sensitivity},\\
V_n^*\left(t-\tau_n\right) &= \textit{desired speed of driver},\\
\left[V_n^*\left(t-\tau_n\right) - V_n\left(t-\tau_n\right)\right] &= \textit{stimulus},\\
\varepsilon_n^{ff}(t) &= \textit{random term associated with free flow}\\
&\quad\ \textit{acceleration of driver n at time t}
\end{aligned}$$

and was estimated to contain the following behavioral parameters:

$$a_n^{ff}(t) = \beta_{sens} \cdot \begin{bmatrix} \alpha + \beta_{fvs} \cdot V_n^{front}(t-\tau_n) - \beta_{hv} \cdot \delta_n^{heavy} \\ + \beta_d \cdot \delta\left[k_n(t-\tau_n)\right] - V_n(t-\tau_n) \end{bmatrix} + \varepsilon_n^{ff}(t) \quad (4\text{-}2)$$

where,

$$\begin{aligned}
\beta_{sens} &= \textit{sensitivity constant},\\
\alpha &= \textit{constant},\\
V_n^{front}(t-\tau_n) &= \textit{front vehicle speed at time } (t - \tau_n),\\
\delta_n^{heavy} &= \textit{heavy vehicle dummy}\\
\delta\left[k_n(t-\tau_n)\right] &= \textit{indicator for density}
\end{aligned}$$

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 4-3.

$$a_n^{cf,g}(t) = s\left[X_n^{cf,g}\left(t-\xi\tau_n\right)\right] f\left[\Delta V_n(t-\tau_n)\right] + \varepsilon_n^{cf,g}(t) \quad (4\text{-}3)$$

where,

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

and was estimated to contain the following behavioral parameters:

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

where,

$$\alpha = constant,$$
$$V_n(t) = subject \ speed \ at \ time \ t,$$
$$\Delta X_n(t) = space \ headway \ at \ time \ t$$
$$k_n(t) = indicator \ for \ density \ ahead \ of \ subject$$
$$\Delta V_n(t-\tau_n) = front \ vehicle \ speed \ - \ subject \ speed$$

Based on a priori knowledge and the literature review, it is expected that the acceleration parameters most affected by adverse weather conditions are the desired speed and the sensitivity of the relative speed of vehicles.

4.3.2 Lane Changing

MITSIM contains two lane changing models, one that distinguishes between discretionary and mandatory lane changing (Ahmed's) and one that is an integrated model, combining the two types, utilizing lane utilities (Toledo's). The more sophisticated integrated model will be used in this study; the structure and functional form is presented below.

Toledo bases his model on three main elements of driving behavior: short-term goal (defined by the driver's target lane), short-term plan (defined by the target gap in the target lane) and the driver's actions, the two dimensional movements (accelerations and lane changes) that the driver performs in order to execute the short-term plan, as shown in Figure 4-3.

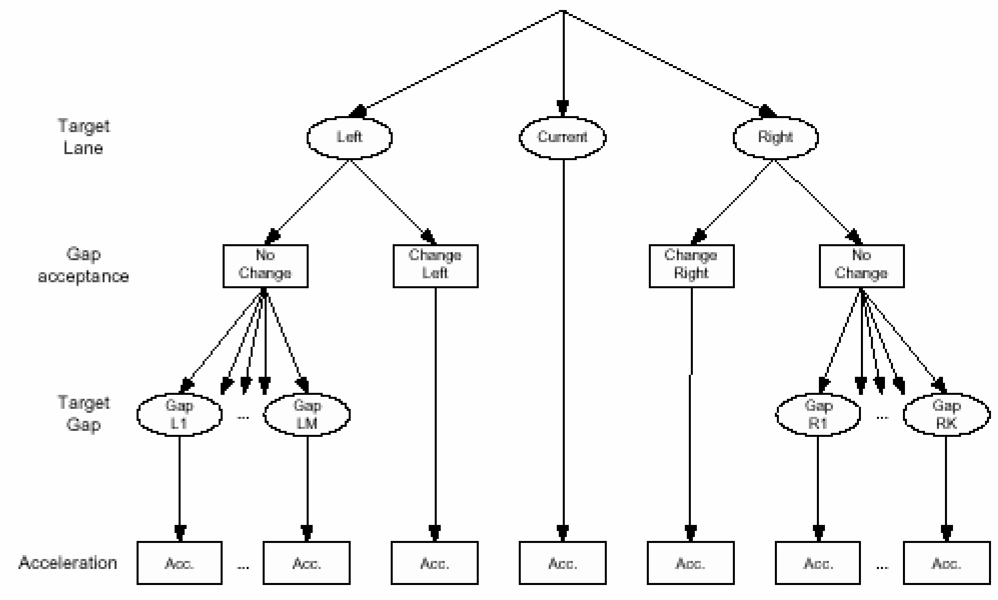

Figure 4-3: Structure of Integrated Lane Changing Model in MITSIM

At the highest level, the driver chooses a target lane. The driver then evaluates the adjacent gap in the target lane and decides whether the gap can be used to execute the lane change. If so, the lane change is executed and the short-term goal is accomplished. If not, the driver evaluates available gaps in the target lane and chooses the one that would be used to perform the desired lane change.

The target lane model consists of a utility function for each of the three possible target lanes, the current lane (CL), the right lane (RL) or left lane (LL), given below:

$$U_n^{CL}(t) = X_n^{CL}(t)\beta^{CL} + \alpha^{CL}v_n + \varepsilon_n^{CL}(t) \quad (4\text{-}5)$$

$$U_n^{RL}(t) = X_n^{RL}(t)\beta^{RL} + \alpha^{RL}v_n + \varepsilon_n^{RL}(t) \quad (4\text{-}6)$$

$$U_n^{LL}(t) = X_n^{LL}(t)\beta^{LL} + \alpha^{LL}v_n + \varepsilon_n^{LL}(t) \quad (4\text{-}7)$$

where, X_n are vectors of explanatory variables affecting the utility of the lane, β are the corresponding vectors of parameters, ε are the random terms associated with the lane utilities, v_n is an individual specific error term and α are the parameters of v_n for each of the current, right and left lanes.

If the utility of one of the adjacent lanes results in it being selected, the driver seeks an acceptable gap in the target lane. Drivers are assumed to have minimum acceptable lead and lag gap lengths, which vary not only by driver, but also among individual under different traffic conditions. The critical gap model for driver n at time t is expressed in Equation 4-8:

$$G_n^{cr,g}(t) = \exp\left(X_n^g(t)\beta^g + \alpha^g v_n + \varepsilon_n^g(t)\right) \quad (4\text{-}8)$$

$$\begin{aligned} g &\in \{lead, lag\}, \\ X_n^g &= \textit{vector of explanatory variables affecting gap acceptance}, \\ \alpha^g &= \textit{parameter of } v_n \textit{ for } g \in \{lead, lag\}, \\ \varepsilon_n^g(t) &= \textit{generic random term that varies across } g, t, \textit{and } n \end{aligned}$$

Model estimation resulted in the following expressions for lane utility:

$$\begin{aligned} V_n^{CL}(t) = {} & \alpha^{CL} + \beta^{rm}\delta_n^{rightmost,CL}(t) + \beta^{vf} V_n^{front}(t) + \beta^{sf} S_n^{front}(t) + \\ & \beta^d d_n^{CL}(t) + \beta^h \delta_n^{hneigh,CL} + \beta^{tg}\delta_n^{tailgate} + \\ & \left[d_n^{exit}\right]^{\beta^{exit}} \left(\beta^1\delta_n^{1,CL}(t) + \beta^2\delta_n^{2,CL}(t) + \beta^3\delta_n^{3,CL}(t)\right) \\ & + \beta^{ne}\delta_n^{ne,CL}(t) + \beta^{add}\delta_n^{add,CL}(t) + \beta^v v_n \end{aligned} \quad (4\text{-}9)$$

$$\begin{aligned} V_n^{RL}(t) = {} & \alpha^{RL} + \beta^{rm}\delta_n^{rightmost,RL}(t) + \beta^d d_n^{RL}(t) + \beta^h \delta_n^{hneigh,RL} + \\ & \left[d_n^{exit}\right]^{\beta^{exit}} \left(\beta^1\delta_n^{1,RL}(t) + \beta^2\delta_n^{2,RL}(t) + \beta^3\delta_n^{3,RL}(t)\right) \\ & + \beta^{ne}\delta_n^{ne,RL}(t) + \beta^{add}\delta_n^{add,RL}(t) + \beta^{emu} EMU_n^{RL}(t) + \beta^{v2} v_n \end{aligned} \quad (4\text{-}10)$$

$$\begin{aligned} V_n^{LL}(t) = {} & \beta^d d_n^{LL}(t) + \beta^h \delta_n^{hneigh,LL} + \\ & \left[d_n^{exit}\right]^{\beta^{exit}} \left(\beta^1\delta_n^{1,LL}(t) + \beta^2\delta_n^{2,LL}(t) + \beta^3\delta_n^{3,LL}(t)\right) \\ & + \beta^{ne}\delta_n^{ne,LL}(t) + \beta^{add}\delta_n^{add,LL}(t) + \beta^{emu} EMU_n^{LL}(t) \end{aligned} \quad (4\text{-}11)$$

where, $EMU^{RL}(t)$ and $EMU^{LL}(t)$ are right and left lane gap acceptance maximum utilities, respectively. The results of the estimation of lead and lag gap are shown in the following expressions:

$$G_{cr,n}^{lead,TL}(t) = \exp\begin{bmatrix} \alpha^{lead} + \beta^{\max}\max\left(0, \Delta V_n^{lead,TL}(t)\right) + \beta^{\min}\min\left(0, \Delta V_n^{lead,TL}(t)\right) \\ + \beta^{emu} EMU_n^{TG,TL}(t) + \beta^v v_n + \varepsilon_n^{lead}(t) \end{bmatrix} \quad (4\text{-}12)$$

$$G_{cr,n}^{lag,TL}(t) = \exp\begin{bmatrix} \alpha^{lag} + \beta^{\max}\max\left(0, \Delta V_n^{lag,TL}(t)\right) + \\ + \beta^{lag,emu} EMU_n^{TG,TL}(t) + \beta^{lag,v} v_n + \varepsilon_n^{lag}(t) \end{bmatrix} \quad (4\text{-}13)$$

where,

$$\Delta V_n^{lead}(t) = lead\ (lag)\ relative\ speed$$

Based on a priori knowledge and literature review, it is expected that lane changing parameters most affected by adverse weather will be the lead and lag critical gaps. Additionally, the desired speed will likely be reduced and the utility of the current lane will likely be affected for discretionary lane changes.

4.4 Discussion of Data

This section describes the data used in the study in more detail, beginning with limitations of available data, analysis of traffic data with weather information, and a basic sensitivity analysis of important driving behavior parameters.

4.4.1 Limitations of Data

The available data has several limitations that may confine the model calibration. Firstly, aggregate data is used for both traffic and weather information.

- **Weather data –** availability of weather data was quite restricted, spatially, temporally and in scope. Weather effects on the roadway segment were inferred based on the weather data from Norfolk International Airport (NIA).
  - NIA is located more than 5 miles from the study area. While the dates were selected for days during which there was continuous precipitation for more than two hours around the study area to minimize the chance that weather conditions at the airport were different from those on the roadway, it does guarantee that weather on the I-265 corridor exactly matches the reading at the airport. This likely has the most influence on the visibility readings as it is much more a localized element.
  - Furthermore, the weather data is collected hourly while traffic data is in 5 minute intervals so error was introduced in the mapping of hourly weather station data to the sensor data.
  - Precipitation, visibility and temperature are the only weather data points available. Other data that may be important and affect driving behavior are pavement conditions and wind speed.

- Given the climate of the Hampton Roads region, all precipitation was rain. Literature indicated that snowy and slushy road conditions have a significant impact on capacity and speed reduction.

- **Incidents –** Information on accidents, special programs and road construction were not available in enough detail (i.e. location and specific lane) to incorporate them into the simulation and therefore were not used in this study. Study dates were selected such that no accidents (based on more than one blocked lane) occurred during the observed time periods. While this has the benefit of reducing incidents as an additional influencing factor and enabling the model to focus explicitly on weather effects, this could under-estimate the impact of weather on driving behavior in terms of reduced speeds and increased congestion and delay, given that 22% of accidents occur due to adverse weather conditions (Goodwin, 2001).

- **Sensor error –** There is inherent error in the sensor data. Upon inspection of the sensor data, it was determined that 12 sensor readings (those not shaded in Table 4-2) could be used for OD estimation (only 1 of which contained incomplete data) and 6 sensors could be used for parameter estimation due to erroneous speed readings. Additionally, no speed readings were greater than 65 mph. It is highly unlikely that with low densities and a high level of service that some vehicles do not travel above the speed limit. Figure 4-4 shows the sensor locations in a schematic of the study area (Smart Travel Lab, 2004).

Table 4-2: I-264 EB Sensor Information

Sensor	Mile-Marker	Roadway	Counts	Speed	Problem
160	15.1	Norm	●	●	
161	15.2	On	●	●	
163	15.3	Off	∅	∅	Some dates missing
165	15.6	Norm	∅	∅	Some dates missing - discard
167	16.1	Norm	●	∅	Some dates default speed of 65
169	16.3	Off	●	●	
172	16.4	Norm	∅	∅	Counts error - discard
173	16.5	On	●	∅	Some dates default speed of 65
175	16.5	Off	●	∅	Most readings default speed of 65

176	16.6	Norm	●	●	
177	16.7	On	●	∅	Most readings default speed of 65
180	17.1	Norm	●	∅	Most readings default speed of 65 - discard
182	17.9	Norm	●	●	
185	18.4	Norm	●	∅	Most readings default speed of 65 - discard
188	18.7	Norm	●	∅	Most readings default speed of 65
189	18.6	Off	●	●	

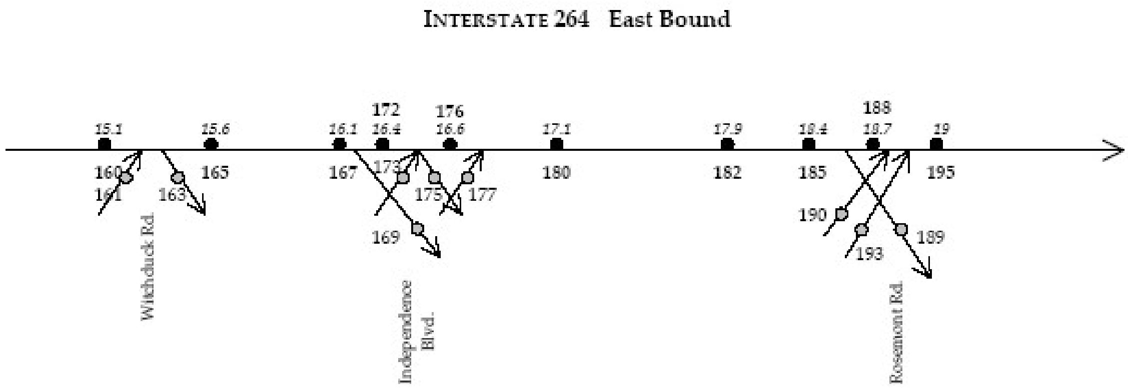

Figure 4-4: Study Area Schematic with Sensor Location

4.4.2 Weather Effects

A University of Virginia study by Byrne, et al (2003), using data from the Hampton Roads study region (sensors on I-64), indicated that there is approximately a 5-6.5% decrease in vehicle speed during the presence of rain (regardless of rain intensity). Therefore, it is assumed that the study area will have similar results.

The six sensors reporting usable speed data were used for analysis. Speed-density plots indicated that speeds on days with precipitation tended to be lower, particularly at higher densities. Figure 4-5 and Figure 4-6 are sample plots from sensors 160 and 182, respectively, on the freeway. As shown in the figures, there are higher densities at sensor 160 than 182 and the speed difference is more apparent.

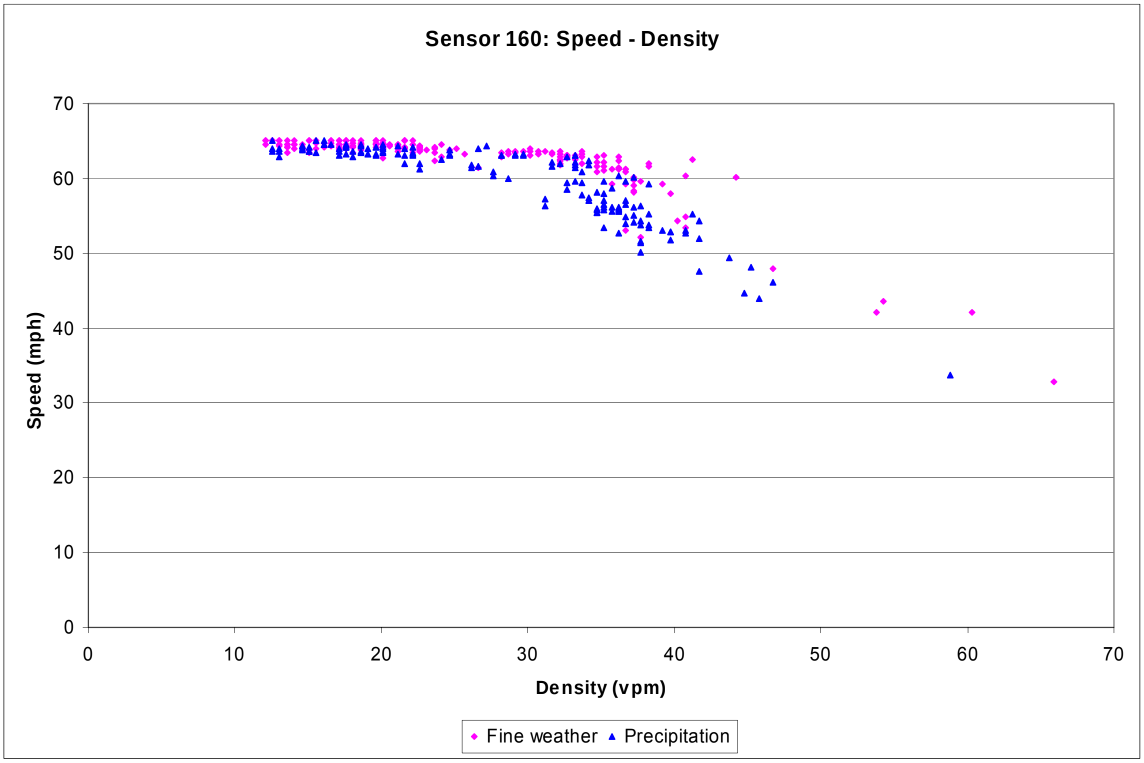

Figure 4-5: Sensor 160 Speed-Density Plot

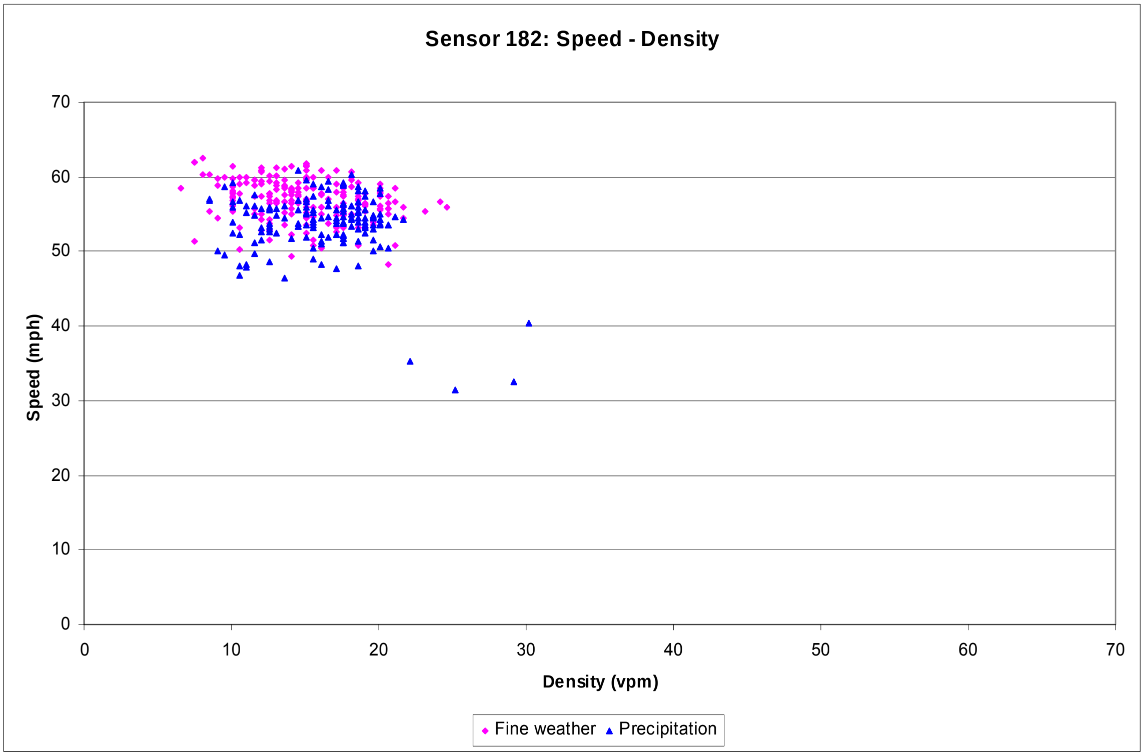

Figure 4-6: Sensor 182 Speed-Density Plot

Three of the sensors with usable speed data are located on entrance or exit ramps. Sensor 169 is an off-ramp located at exit 17a - Figure 4-7 shows quite a defined speed-density curve, with speeds tending to be lower on days with precipitation than on those without.

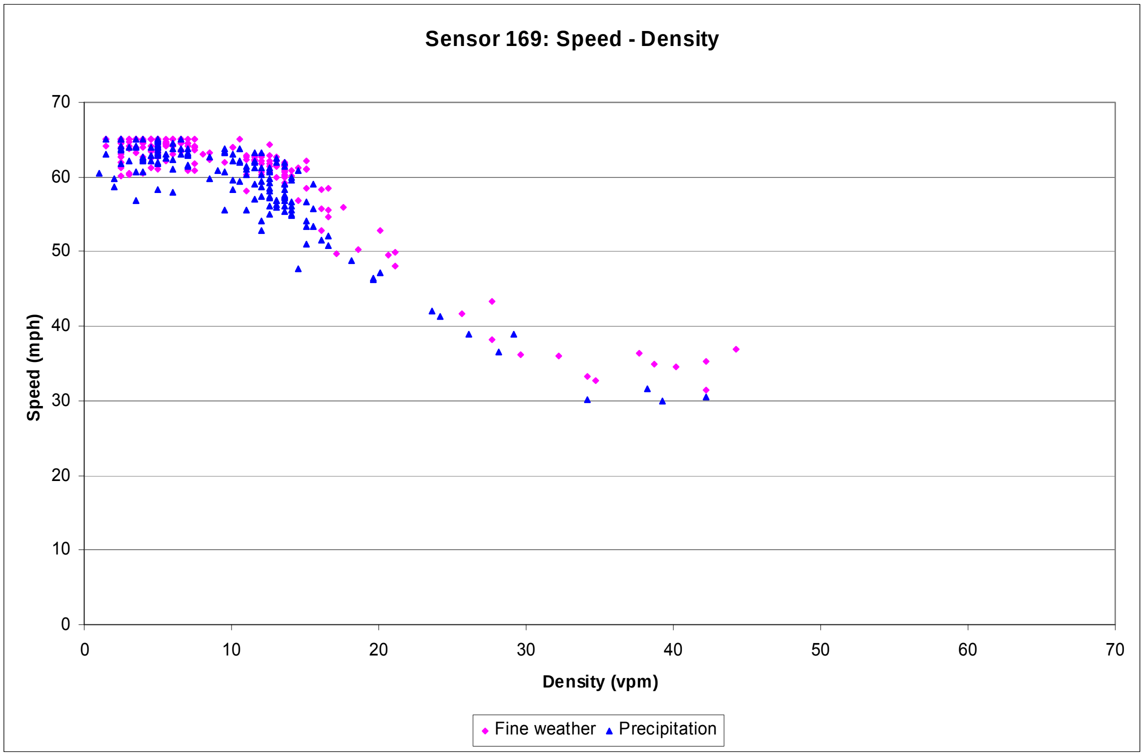

Figure 4-7: Sensor 169 Speed-Density Plot

Given this initial investigation of the data, regression analysis was performed to quantify the effect of weather on speed and confirm that it is in fact a significant factor. Several studies have been undertaken to quantify the impacts of weather on travel behavior. A FHWA Road Weather Management Program study in the Washington, DC metropolitan area attempted to quantify the amount of travel delay due to the effects of adverse weather (Stern, et al, 2003). Similarly to this thesis, the study used hourly weather data with travel time data in five minute intervals and used a two-step linear regression process to predict travel times based on the following weather variables:

Table 4-3: Observational Elements in FHWA DC Regression Analysis

Description	Classifications	
Precipitation type and intensity	None Light rain/snow	Heavy rain Heavy snow/sleet
Sustained wind speed	< 30 mph	≥ 30 mph
Visibility distance	≥ 0.25 miles	< 0.25 miles
Pavement condition	Dry Wet	Snow/Ice Black ice

The study indicated that pavement condition and precipitation were the most important explanatory variables, finding a R^2 value of 0.23, on average.

A study of traffic flow-density relationship by Kockelman (1998) explored the influences of weather conditions, as well as driver- and vehicle-population characteristics, using a third-order-polynomial regression, with linear functions of explanatory variables. A dummy variable for observations that occurred during rainfall was used, and was found to be significant, resulting in lower flows.

With these studies as a starting point, regression analysis to predict travel speed was performed with available data. Several regression models were tested. Of particular interest is the insignificance of visibility across the all model formulations. Table 4-4 presents a sample of statistics demonstrating that visibility is insignificant in this data set. Also worthy of mention is that the sign of the coefficient for many sensors is not as expected and indicates that speed decreases as visibility increases. However, the magnitude of the coefficient is quite small, resulting in less than a half of a mph change in speed. Since it contradicts a priori estimates and literature, it is likely that the quality of weather data has a significant effect on this phenomenon, as visibility is quite dependent on geography and location.

Table 4-4: Sample Statistics for Visibility

	160		176		182	
R Square	0.001		0.003		0.004	
	Coef	*t Stat*	*Coef*	*t Stat*	*Coef*	*t Stat*
Intercept	61.6	121	58.3	485	55.3	138
Visibility (mi)	-0.039	-0.559	-0.017	-1.054	0.064	1.161
	161		**169**		**189**	
R Square	0.000		0.000		0.000	
	Coef	*t Stat*	*Coef*	*t Stat*	*Coef*	*t Stat*
Intercept	38.3	90	38.3	90	59.5	169
Visibility (mi)	-0.004	-0.069	-0.004	-0.069	0.015	0.316

Regressions using both actual precipitation rates and precipitation categories were tested. A linear model including density and precipitation showed the best fit across all sensors, with precipitation significant for all sensors. The results for the regression with density and precipitation amounts (in/hr) for mainline and ramps are shown in Table 4-5 and Table 4-6, respectively.

Table 4-5: Regression Results for Mainline Sensors

Sensor:	**160**		**176**		**182**	
Multiple R	0.835		0.558		0.634	
R Square	0.697		0.312		0.402	
Adjusted R Square	0.695		0.308		0.398	
Standard Error	2.68		0.951		2.96	
Observations	360		360		360	
Parameters	***Coef***	***t Stat***	***Coef***	***t Stat***	***Coef***	***t Stat***
Intercept	72.5	174	60.8	285	60.4	89
Density	-0.393	-26.95	-0.145	-12.58	-0.222	-5.14
Precipitation	-36.9	-7.12	-3.94	-2.15	-78.1	-13.5

Table 4-6: Regression Results for On- and Off-ramp Sensors

Sensor:	**161**		**169**		**189**	
Multiple R	0.644		0.919		0.594	
R Square	0.415		0.845		0.353	
Adjusted R Square	0.412		0.845		0.349	
Standard Error	3.08		2.852		2.71	
Observations	360		360		360	
Parameters	***Coef***	***t Stat***	***Coef***	***t Stat***	***Coef***	***t Stat***
Intercept	45.9	90	68.8	271	64.6	155
Density	-0.529	-15.50	-0.819	-41.78	-0.179	-11.0
Precipitation	-21.0	-3.54	-39.10	-7.02	-44.0	-8.46

The results for the regression with density and precipitation categories for mainline and ramps are shown in Table 4-7 and Table 4-8 respectively.

Table 4-7: Regression Results for Mainline Sensors

Sensor	**160**		**176**		**182**	
Multiple R	0.832		0.554		0.496	
R Square	0.693		0.307		0.246	
Adjusted R Square	0.691		0.303		0.241	
Standard Error	2.70		0.955		3.33	
Observations	360		360		360	
	Coef	*t Stat*	*Coef*	*t Stat*	*Coef*	*t Stat*
Intercept	72.6	172	60.8	284	60.8	80
Density	-0.387	-26.14	-0.143	-12.44	-0.250	-5.13
Precipitation - C	-1.95	-6.70	-0.143	-1.41	-3.02	-8.37

Table 4-8: Regression Statistics for On- and Off- Ramps

Sensor	161		169		189	
Multiple R	0.638		0.913		0.535	
R Square	0.407		0.833		0.287	
Adjusted R Square	0.403		0.833		0.283	
Standard Error	3.10		2.96		2.84	
Observations	360		360		360	
	Coef	*t Stat*	*Coef*	*t Stat*	*Coef*	*t Stat*
Intercept	45.8	90	68.9	243	64.4	146
Density	-0.522	-15.12	-0.836	-41.57	-0.174	-10.1
Precipitation - C	-0.898	-2.71	-1.421	-4.50	-1.70	-5.62

As shown in the tables above the two models show very similar descriptions of speeds, decreasing speed up to 5%. Precipitation was statistically significant (for all but sensor 176, which was significant at an 85% confidence interval). The University of Virginia study of this region indicated that rain intensity had no affect on speed reduction, but presence of rain was a key factor. Both the Kockelman study and the Mitretek/FHWA study used presence of rain, rather than precipitation amount. These studies, coupled with the fact that the weather data may not exactly represent the conditions at each sensor, provides motivation to classify the precipitation data. Additionally, it is more likely that the exact value of precipitation will be unknown in planning applications.

The Virginia study classified precipitation into light and heavy rain based on recommendations from the Cooperative Institute of Meteorological Satellite Studies (Byrne, et al, 2003), shown in Table 4-9. These classifications will be used in this study as well.

Table 4-9: Precipitation Intensity Classification

Rain Intensity	Rainfall (in/hr)
None	< 0.01
Light	0.01 – 0.25
Heavy	> 0.25

A regression model including only the effects of precipitation was tested - the variable was significant (again, for all but Sensor 176, which was significant at 85% confidence interval), but the R^2 value was significantly lower, indicating that, intuitively, just precipitation is not a valid predictor for speed. However, since the driving behavioral models include density and other factors already estimated and validated with disaggregate data, precipitation is sufficient as an explanatory variable for the weather conditions.

4.4.3 Sensitivity Analysis of Behavior Parameters

Based on the literature review and knowledge of driving behavior models, four key components of driving behavior were identified as being most critical in driving behavior in MITSIMLab: free flow acceleration, car following acceleration, lane changing, and gap acceptance. Within these four models, eight parameters were identified, as shown in Table 4-10. A sensitivity analysis was performed, isolating each model while keeping all other parameters at their original values, to measure the impact of the individual factors on the overall predictive quality of the system.

Table 4-10: Behavior Parameter Sensitivity Analysis

Model & Parameter	Ahmed and Toledo's Estimated Parameter Value	% Improvement
Acceleration		
Free flow - Desired speed distribution*		
Mean of distribution around SL	-	6.9%
Distribution in population	-	
Car following		
Acc constant (alpha)	0.0400	17.7%
Dec constant (alpha)	-0.0418	
Lane Changing - Utility		
Current lane constant	3.9443	0.0%
Right lane constant	-0,3213	
Gap Acceptance		
Lead constant	0.5	4.1%
Lag constant	0.5	

* Desired speed distribution parameters were estimated by Ahmed (1999). The aggregate calibration results are based on a standard normal distribution.

The sensitivity analysis results indicated that the car following parameters had by far the most impact on simulating driver behavior. In addition, the desired speed distribution and gap acceptance models resulted in a marginal improvement. Interestingly, lane changing utility did not significantly impact the overall quality of the simulation.

Given this sensitivity analysis, parameters for the car following model (the acceleration and deceleration constants), free flow acceleration (desired speed distribution) and the gap acceptance models will be included in the calibration. The weather model will also include parameters specific to the weather condition for car-following, speed distribution, and gap acceptance. Calibration results are presented in Chapter 5.

Chapter 5
Results

This chapter presents results of OD estimation and driving parameter calibration for a base case and one including parameters to account for the presence of precipitation. An initial origin-destination matrix was estimated using the available sensor counts. Given that the study area is a corridor, route choice is eliminated, and the aggregate calibration procedure is simplified. The driving parameters estimated by Ahmed and Toledo were used as the starting point in parameter calibration.

5.1 OD Estimation

OD estimation was performed for both the AM and PM periods of observation. Figure 5-1 and Figure 5-2 present plots of observed counts versus simulated counts for AM and PM periods, respectively. As the figures show, both periods have unbiased results that indicate the simulation represents the real-world conditions.

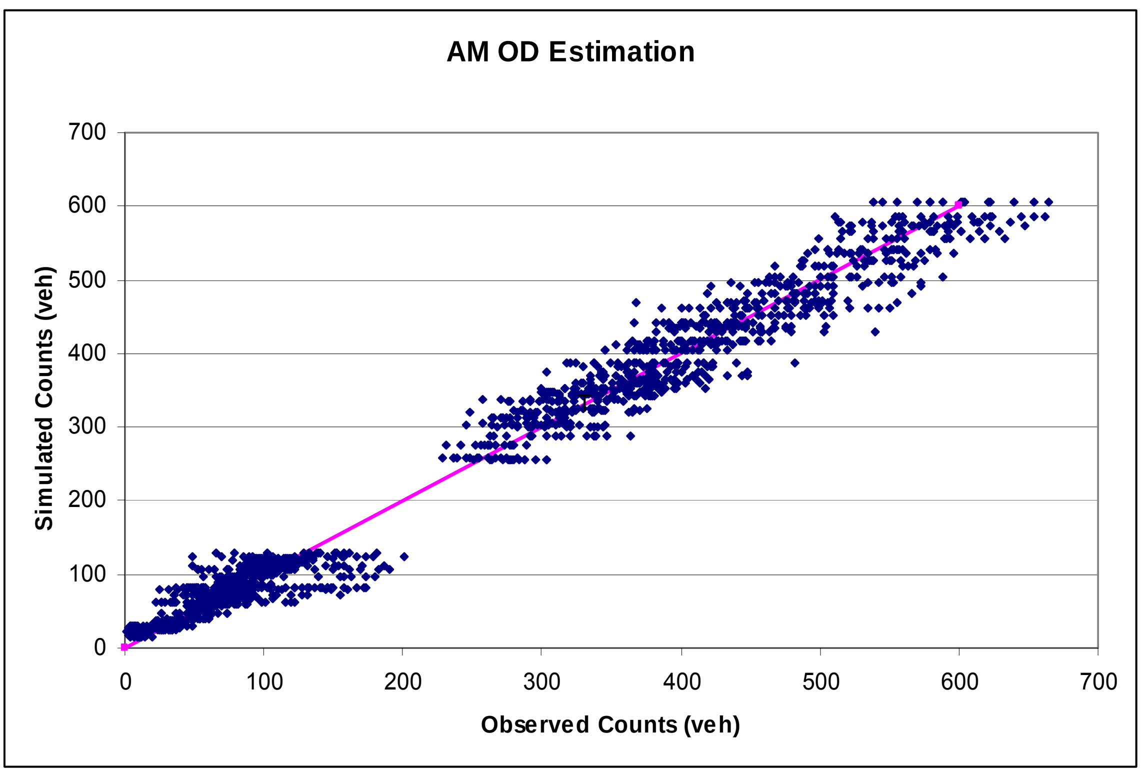

Figure 5-1: AM Observed vs Simulated Counts

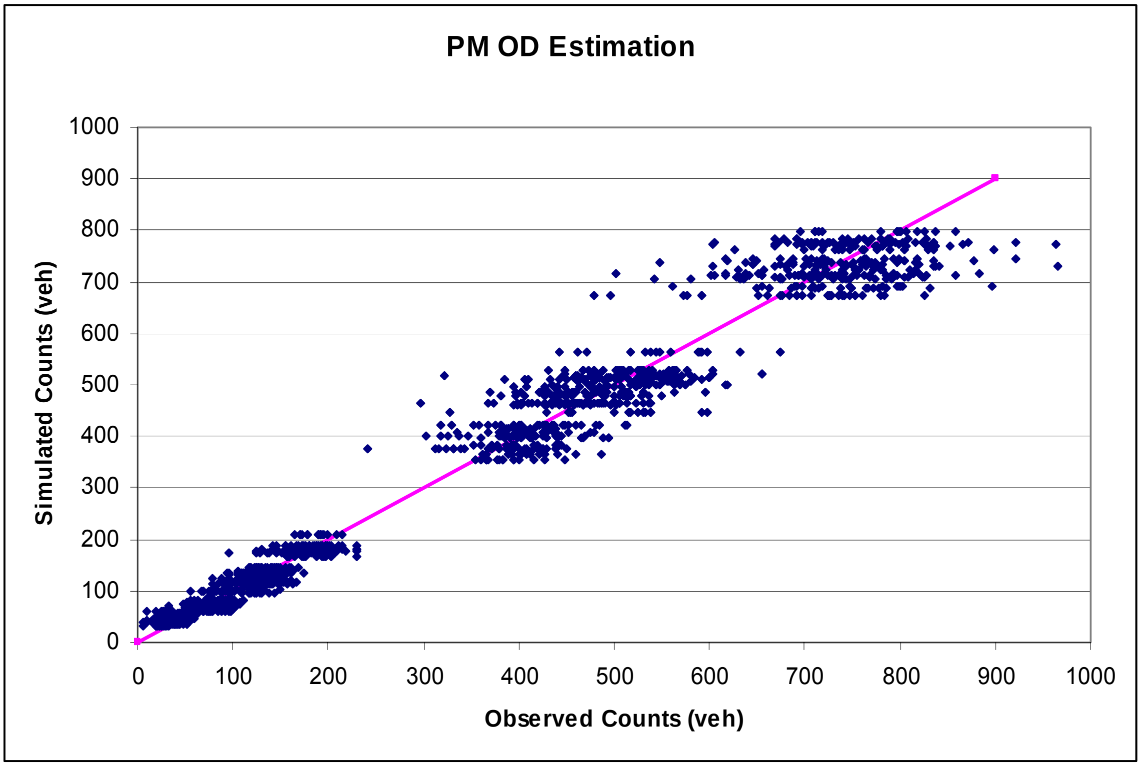

Figure 5-2: PM Observed vs Simulated Counts

Table 5-1 presents the goodness-of-fit statistics of OD estimation.

Table 5-1: Statistics for AM and PM OD Estimation

Statistic	AM	PM
RMS	25.2	39.9
RMSN	11.9%	13.6%
U (Theil's inequality coefficient)	0.0449	0.0513
U^M (bias proportion)	0.0030	0.0002
U^S (variance proportion)	0.0131	0.0127
U^C (covariance proportion)	0.9839	0.9871

Theil's inequality coefficient indicates a very good fit between observed and simulated measurements (as 0 implies a perfect fit). As expected, the bias and variance portions of the inequality were quite low, indicating an unbiased simulation that is able to replicate the variability of the observed data.

5.2 Parameter Estimation

Per results of the literature review and sensitivity analysis described in Chapter 4, a set of parameters for car following acceleration and deceleration, the desired speed distribution and gap acceptance were estimated for this study area and conditions. The existing models were calibrated in order to fine-tune the model for the study location and act as a base for comparison with the model incorporating weather factors. Table 5-2 presents the results of the base parameter calibration.

Table 5-2: Base Model Parameters

Model & Parameter	Value
Acceleration	
Free flow - Desired speed distribution*	
Mean of distribution around SL	0.0462
Distribution in population	0.0811
Car following	
Acceleration constant (alpha)	0.2228
Deceleration constant (alpha)	-0.0416
Gap Acceptance	
Lead constant	0.4451
Lag constant	0.6721

*See Table 5-4 for speed distribution results

Given that the study location data varies from the trajectory data used to estimate the models, it is not surprising that some parameters differ somewhat from values originally estimated for Ahmed and Toledo's models. However, it is important to ensure that the results of the calibration are realistic. All of the parameters are intuitive and conform to previously estimated ranges. The acceleration constant is significantly higher than the value estimated by Ahmed, but is within the range of values that were discussed in the dissertation (Ahmed, 1999). The deceleration constant is quite close to that estimated originally by Ahmed. The values estimated to form the desired speed distribution result in a typical distribution curve as estimated previously. The critical gap constants are within the same order of magnitude as those estimated and validated in Toledo's dissertation, but with a slightly lower lead constant and a slightly higher lab constant, indicating slightly more aggressive and conservative gap acceptance for lead and lag gaps, respectively.

As described in Chapter 4, the effects of weather were incorporated into the model using a variable to reflect the presence (and intensity, however the data set was limited to light rain conditions) of rain. In addition to the parameters described above in the base model, parameters designed to capture the effect of weather for acceleration, desired speed distribution and critical gaps, were estimated. In other words, the overall value for each parameter was estimated as

$$\alpha^{i} = \alpha_{0}^{i} + \beta^{wi} \cdot W \quad (5\text{-}1)$$

where, i represents the model (car-following, desired speed, gap acceptance), α is the parameter of interest for each model, W is the presence of rain (0 or 1), and β is the parameter associated with the affects of rain and is applied to the relevant models as described below.

For the free-flow desired speed distribution, each of the estimated parameters (mean of the distribution above the speed limit and the distribution around the speed limit) are used with a weather parameter to determine the appropriate desired speed distribution for the enhanced model. So, the desired speed is determined as follows:

$$DS_{i} = \left(\mu_{i} + \beta^{m,w} \cdot W\right) + \left(\sigma_{i} + \beta^{s,w} W\right) \cdot Z_{i} \quad (5\text{-}2)$$

where, i is the percentile from 5% to 95%. The car following and gap acceptance models are modified from those originally estimated by Ahmed and Toledo, respectively, to incorporate weather as shown in the following expressions.

$$\begin{aligned} a_{n}^{cf,acc}(t) &= \left(\alpha + \beta^{a,w} W\right) \cdot \frac{V_{n}(t)^{\beta_{s}}}{\Delta X_{n}(t)^{\beta_{h}}} \cdot k_{n}(t)^{\beta_{d}} \left|\Delta V_{n}(t-\tau_{n})\right|^{\beta_{rs}} + \varepsilon_{n}^{cf,acc}(t) \\ a_{n}^{cf,dec}(t) &= \left(\alpha + \beta^{a,w} W\right) \cdot \frac{1}{\Delta X_{n}(t)^{\beta_{h}}} \cdot k_{n}(t)^{\beta_{d}} \left|\Delta V_{n}(t-\tau_{n})\right|^{\beta_{rs}} + \varepsilon_{n}^{cf,dec}(t) \end{aligned} \quad (5\text{-}3)$$

$$G_{cr,n}^{lead,TL}(t) = \exp\left[\begin{array}{l} \left(\alpha^{lead} + \beta^{g,w} W\right) + \beta^{\max} \max\left(0, \Delta V_{n}^{lead,TL}(t)\right) + \\ \beta^{\min} \min\left(0, \Delta V_{n}^{lead,TL}(t)\right) + \beta^{emu} EMU_{n}^{TG,TL}(t) + \beta^{v} v_{n} + \varepsilon_{n}^{lead}(t) \end{array}\right] \quad (5\text{-}4)$$

$$G_{cr,n}^{lag,TL}(t) = \exp\left[\begin{array}{l} \left(\alpha^{lag} + \beta^{g,w} W\right) + \beta^{\max} \max\left(0, \Delta V_{n}^{lag,TL}(t)\right) + \\ + \beta^{lag,emu} EMU_{n}^{TG,TL}(t) + \beta^{lag,v} v_{n} + \varepsilon_{n}^{lag}(t) \end{array}\right] \quad (5\text{-}5)$$

Table 5-3 presents the results of parameter calibration for this model.

Table 5-3: Parameter Calibration Results Including Effects of Weather

Model & Parameter	Value in Fine Weather, W = 0 ($\alpha+\beta(0)$)	Value in Rain, W = 1 ($\alpha+\beta(1)$)
Acceleration		
Free flow - Desired speed distribution*		
Mean of distribution around SL	0.0478	0.0238
Distribution in population	0.0039	0.0745
Car following		
Acc constant (alpha)	0.2862	0.2147
Dec constant (alpha)	-0.0044	-0.0760
Gap Acceptance		
Lead constant	0.2742	0.5234
Lag constant	0.5222	0.7714

The results of this estimation also are intuitive and agree with the literature on the subject. Acceleration and deceleration is negatively affected by the presence of precipitation, while the critical gap is increased. This indicates more cautious car-following behavior. When the driver has the opportunity to accelerate, he or she does so in a more conservative fashion in adverse weather conditions. Similarly, when conditions require that the driver slow, they demonstrate more caution by decelerating more when there is precipitation. Additionally, the mean of desired speed distribution around the speed limit decreases, indicating more conservative free-flow behavior in inclement conditions. The reduction in the mean of the desired speed supports the literature review. However, the spread of the distribution increases in the presence of rain. The increase in spread over the mean can be explained by the varying aggressiveness of drivers – while many drivers do change behavior based on environmental conditions, some do not, increasing the overall distribution. Gap acceptance results also indicate more conservative lane-changing behavior. Drivers require a larger lead and lag gap in inclement weather than in fine weather conditions, indicating increased caution.

It is also important to compare the new model results with the base model. As expected, the base model parameter values are within the range of those parameters estimated for fine and inclement weather for the car-following and gap acceptance models. The mean of the desired speed over the speed limit in the base model also is within the range of the two means in the enhanced model, as expected. However, the distribution in the base model is significantly higher, particularly relative to the distribution when there is no precipitation. This indicates that factors causing lower speeds and higher variance can be captured in other parameters, namely, the effects of precipitation, and lends further evidence that adverse weather is an important factor in driving behavior and introduces variability.

Table 5-4: Desired Speed Distribution Calibration

Percentile	Base	Including Weather	
		Fine	Precipitation
0.05	-0.0873	0.0413	-0.0987
0.15	-0.0379	0.0437	-0.0534
0.25	-0.0085	0.0451	-0.0264
0.35	0.0149	0.0463	-0.0049
0.45	0.0359	0.0473	0.0144
0.55	0.0564	0.0483	0.0332
0.65	0.0774	0.0493	0.0525
0.75	0.1008	0.0504	0.0740
0.85	0.1302	0.0519	0.1010
0.95	0.1796	0.0542	0.1464

Table 5-5 presents statistics useful for comparing the effectiveness of the model incorporating weather factors.

Table 5-5: Statistics for Speed Comparison in Hampton Roads, Virginia

Statistic	**Base**	**With Weather Effects**
RMS	8.11	7.80
RMSN	14.9%	14.5%
U (Theil's inequality coefficient)	0.0768	0.0738
U^M (bias proportion)	0.2746	0.1798
U^S (variance proportion)	0.1354	0.0907
U^C (covariance proportion)	0.5900	0.7295

The statistics for measures of effectiveness indicate that the weather model performed better than the base model without the external factors. Both root mean square error and the normalized root mean square error indicate the overall error of the simulator is reduced by including the effects of weather. The enhanced model resulted in an approximately 5% improvement in root mean square value. Additionally, and more significantly, Theil's inequality coefficient demonstrates a large benefit with the enhanced model. Both models result in a coefficient indicating a good fit between observed and simulated measurements (the weather model more so). However, the proportions of the inequality show significant improvement with the enhanced model. The base model shows bias and tends to under-estimate speeds on fine days as it does not distinguishing weather as an external factor. The bias proportion is improved by 35%. The variance proportion is also better (by 33%) in the enhanced model, indicating the model better replicates variability in the observed data.

5.3 Recommendations

Despite significant limitations of both traffic sensor data and detailed weather data, the enhanced model incorporating the external effects of precipitation conditions preformed significantly better than the model without the explanatory weather factors. The Federal Highway Administration's Road Weather Management Program has placed a priority on obtaining better weather information. Research, such as this, on the impact of weather on travel speeds, roadway capacity is a critical element in improving overall network operations and system efficiency and reliability by providing tools and knowledge to traffic management centers.

One of the program initiatives is the installation and utilization of environmental sensing stations (ESS), sensors at locations along the roadway that collect atmospheric (visibility, wind speed, precipitation type and rate) and pavement data (temperature and condition – e.g. wet, icy, flooded). The weather data supplied with these sensor stations can be matched to traffic sensors in the roadway and will provide a more detailed and comprehensive description of weather conditions and important influencing factors. As this detailed weather data (both type and location of information) becomes available, the aggregate calibration approach applied in this study can certainly be enhanced and improved upon. Additionally, since driving behavior, especially with respect to weather, is so location-specific, other study areas should be evaluated, particularly those with snowy and icy conditions.

Chapter 6
Conclusions

6.1 Summary

Microscopic simulation provides a solid, sophisticated and efficient environment for transportation analysis. However, most state-of-the-art microscopic traffic simulation tools capabilities in simulating the real-world are limited. The reason for these gaps is primarily lack of data and knowledge, not physical resources. While it is known that many external factors influence driving behavior, the extent to which these impact traffic is known on a macroscopic level. The implications on driving behavior models are mostly unknown.

This thesis has developed a framework to fill such gaps by incorporating influencing factors in a microscopic traffic simulation environment using available aggregate data. Aggregate calibration was used to modify existing driving behavior models with additional explanatory variables. The approach was tested in a case study using weather conditions in the Hampton Roads region of Virginia.

The aggregate calibration methodology applied to weather conditions showed that both the external weather factor and the calibration approach resulted in significant improvement of the model for the case study location, improving the root mean square error by 5%. Inclusion of the weather explanatory variable resulted in a better model performance with regard to predictability of speeds and the enhanced model reduced the bias and variability by 35% and 33%, respectively, that occurred with the original model. Despite limited weather data and limitations of the sensor data, this approach demonstrated promise and can likely be enhanced as more detailed data regarding the explanatory factors weather data becomes available. Additionally, it is likely that other influencing factor not

The aggregate calibration approach is not restricted to systematic environmental impacts such as weather, but has potential to improve the performance of microscopic simulation tools by incorporating other influencing factors in the driving behavior models. Results of the survey on the state-of-the-practice in microscopic traffic simulation revealed many such external factors that may be integrated with this approach. For example, work zone and incidents, two primary contributors to non-recurring traffic congestion, are likely candidates for this type of inclusion. Knowledge of the impact of these events on transportation systems, and specifically driver behavior and reaction, is critical to efficient transportation systems operation. These events are critical but detailed data about the microscopic impacts are unknown, making it an ideal candidate for study with the approach presented in this thesis.

6.2 Future Research

Driving behavior models and transportation analysis tools are only as high-quality as the data available to estimate, calibrate, and validate them. As more detailed trajectory data and more extensive aggregate data is collected, these models can be refined to incorporate more influencing factors and better represent real-world conditions, which is vital for efficient traffic management, contingency planning, and long-term land use planning.

The literature review and survey of existing traffic simulation capabilities indicated there are still critical gaps. In order to capture the effects of geometry, incidents, work zones and weather, data about the relevant factors needs to be collected along with detailed trajectory data. Data collection should be performed in facilities with different geometric characteristics, under varying weather conditions and also include periods of time where incidents and work are present. Once such data is available, the relevant factors can be explicitly represented as explanatory variables in the models that will be developed using disaggregate estimation and validation. This kind of data collection effort is not an easy (or inexpensive) task, and thus makes this type of model estimation and calibration a long-term goal.

However, until detailed disaggregate data is available, a shorter-term goal of using aggregate data to enhance existing behavior models and improve traffic simulation capabilities can be investigated. This thesis developed one approach of refining existing behavior models using available aggregate data and calibration methods and applied it to weather conditions, one of many influencing factors found to be lacking in existing traffic simulation tools. Driving behavior and conditions is very site-specific and therefore estimation results are not necessarily transferable, but application of the methodology and calibration process should be. There is certainly a need for further investigation into this type of approach and development of other approaches to include external factors into driving behavior models and simulation tools.

Appendix A

Influencing Factors in Microsimulation Questionnaire

Simulation of Network

A. Link Characteristics

Please answer the questions below for each of the following link characteristics:

❒ Horizontal curves
❒ Facility type (e.g. freeway, urban street, tunnel, bridge, elevated road)
❒ Lane widths
❒ Median characteristics
❒ Shoulder characteristics
❒ Grade and grade changes
❒ Pavement quality
❒ Auxiliary lanes (e.g. taper, parallel)
❒ Route restrictions / lane use privileges
❒ Sight restrictions
❒ Other (please specify) ______________________________

1. Does your model contain parameters for the link characteristic? Please be specific.

2. How do you represent the link characteristic in the model? Please be specific – explain both explicit and proxy approaches.

3. How does the characteristic (and corresponding parameters) affect driver behavior?

❒ Acceleration ______________________________
❒ Lane Changing ______________________________
❒ Route choice ______________________________
❒ Other (please specify) ______________________________

4. What are the limitations associated with your approach to modeling this characteristic?

Further comments on simulation of links…

B. Intersection Characteristics

Please answer the questions below for each of the following geometric features of intersections:

❒ Angle between links (e.g. 90°, 60°)

- ❐ Flared lanes approaching the intersection (turn pockets)
- ❐ Traffic calming static obstacles (e.g. flower-beds, concrete islands, curbs)
- ❐ Other (please specify) ____

1. Does your model contain parameters for the intersection characteristic? Please be specific.

2. How do you represent the intersection characteristic in the model? Please be specific – explain both explicit and proxy approaches.

3. How does the characteristic (and corresponding parameters) affect driver behavior?

- ❐ Acceleration ____
- ❐ Lane Changing ____
- ❐ Route choice ____
- ❐ Other (please specify) ____

4. What are the limitations associated with your approach to modeling this characteristic?

Further comments on simulation of intersections…

Simulation of System Management

C. Response to Traveler Information

1. In your model, how does traveler information affect drivers' behavior?

- ❐ Route Choice
- ❐ Other (please specify)

2. Does your model contain parameters for the **type** of traveler information? Please be specific.

- ❐ Traveler Information
- ❐ Route guidance
- ❐ Other (please specify)

3. How do you represent the type of traveler information in the model? Please be specific – explain both explicit and proxy approaches.

4. Does your model contain parameters for the **means** of obtaining traveler information? Please be specific.

- ❐ Broadcast (e.g. HAR)
- ❐ Location based (e.g. VMS)
- ❐ Individual (e.g. on-board device)
- ❐ Other (please specify) ____

5. How do you represent the means of traveler information in the model? Please be specific – explain both explicit and proxy approaches.

6. What are the limitations associated with your approach to modeling driver response to traveler information?

Further comments on simulation of response to traveler information…

Simulation of Environment

D. Incidents

1. What are the incident inputs in your model?

Please answer the questions below for each of the following incident characteristics:

- ❒ System effects
  - ❍ Lane closures
  - ❍ Shoulder use / closure
  - ❍ Distractions
  - ❍ Other (please specify) ______________________________
- ❒ Behavioral effects
  - ❍ Emergency braking
  - ❍ Rubber-necking (same and opposite direction)
  - ❍ Other (please specify) ______________________________

2. Does your model contain parameters for the incident characteristic? Please be specific.

3. How do you represent the incident characteristic in the model? Please be specific – explain both explicit and proxy approaches.

4. How does the characteristic (and corresponding parameters) affect driver behavior?

- ❒ Acceleration ______________________________
- ❒ Lane Changing ______________________________
- ❒ Route choice ______________________________
- ❒ Other (please specify) ______________________________

5. What are the limitations associated with your approach to modeling this characteristic?

Further comments on simulation of incidents…

E. Work Zones

1. What are the work zone inputs in your model?

Please answer the questions below for each of the following work zone characteristics:

- ❒ System effects
  - ❍ Reduced speeds / variable speed limits
  - ❍ Lateral clearance
  - ❍ Lane shifts
  - ❍ Lane width reductions

- Reduced shoulder
- Pavement markings
- Other (please specify) ____

❒ Behavioral effects
- Emergency breaking
- Rubber-necking
- Visual distractions
- Aural distractions
- Other (please specify) ____

2. Does your model contain parameters for the work zone characteristic? Please be specific.

3. How do you represent the work zone characteristic in the model? Please be specific – explain both explicit and proxy approaches.

4. How does the characteristic (and corresponding parameters) affect driver behavior?

❒ Acceleration ____
❒ Lane Changing ____
❒ Route choice ____
❒ Other (please specify) ____

5. What are the limitations associated with your approach to modeling this characteristic?

Further comments on simulation of work zones…

F. Weather

Please answer the questions below for each of the following weather characteristics:

❒ Conditions
- Wind
- Rain
- Fog
- Snow
- Ice
- Lighting
- Other (please specify)

❒ System effects
- Reduced visibility (e.g. fog)
  - System wide
  - Localized
- Reduced surface quality (e.g. ice)
  - System wide
  - Localized
- Other (please specify) ____

❒ Behavioral effects
- Emergency breaking
- Skidding

- Other (please specify) ____________________

1. Does your model contain parameters for the weather characteristic? Please be specific.

2. How do you represent the weather characteristic in the model? Please be specific – explain both explicit and proxy approaches.

3. How does the characteristic (and corresponding parameters) affect driver behavior?

- ❒ Acceleration ____________________
- ❒ Lane Changing ____________________
- ❒ Route choice ____________________
- ❒ Distinctive behavior – Skidding ____________________
- ❒ Other (please specify) ____________________

4. What are the limitations associated with your approach to modeling this characteristic?

Further comments on simulation of weather…

Simulation of Vehicle

G. Vehicle Characteristics

Please answer the questions below for each of the following vehicle characteristics:

- ❒ Vehicle dimensions
  - Width
  - Length
  - Height
- ❒ Articulated vehicle sections
- ❒ Vehicle mass
- ❒ Passenger capacity
- ❒ Acceleration and deceleration capabilities
- ❒ Speed capabilities
- ❒ Turning radii
- ❒ Other (please specify) ____________________

1. Does your model contain parameters for the vehicle characteristic? Please be specific.

2. How do you represent the vehicle characteristic in the model? Please be specific – explain both explicit and proxy approaches.

3. How does the characteristic (and corresponding parameters) affect driver behavior?

- ❒ Acceleration ____________________
- ❒ Lane Changing ____________________
- ❒ Route choice ____________________
- ❒ Other (please specify) ____________________

4. What are the limitations associated with your approach to modeling this vehicle characteristic?

Please answer the questions below for each of the following vehicle types:

- ❒ Passenger vehicles
  - ❍ Automobiles
  - ❍ Guided (intelligent) vehicles
  - ❍ SUVs
  - ❍ Taxis
  - ❍ Motorcycles
- ❒ Commercial vehicles
  - ❍ Emergency vehicles
  - ❍ Large trucks
  - ❍ Heavy equipment
  - ❍ Small trucks / vans
- ❒ Transit vehicles
  - ❍ Buses
  - ❍ Minibuses
  - ❍ Trains
  - ❍ Light rail / trams
- ❒ Non-motorized vehicles
  - ❍ Bicycles
  - ❍ Pedestrians
- ❒ Other (please specify) ______________________________

5. Does your model contain distinct behavior parameters for the vehicle type? Please be specific.

6. What are the vehicle characteristics that define the vehicle type?

- ❒ Vehicle dimensions ______________________________
- ❒ Articulated vehicle sections ______________________________
- ❒ Vehicle mass ______________________________
- ❒ Passenger capacity ______________________________
- ❒ Acceleration and deceleration capabilities ______________________________
- ❒ Speed capabilities ______________________________
- ❒ Turning radii ______________________________
- ❒ Other (please specify) ______________________________

7. How is the driver behavior of vehicles interacting with the vehicle type affected?

- ❒ Acceleration ______________________________
- ❒ Lane Changing ______________________________
- ❒ Route Choice ______________________________
- ❒ Other (please specify) ______________________________

8. What are the limitations associated with your approach to modeling this vehicle type?

Further comments on simulation of vehicles…

Simulation of Traveler

H. Traveler Characteristics

Please answer the questions below for each of the following traveler characteristics:

- ❒ Perception
  - ❍ Visual acuity of drivers
  - ❍ Attentiveness of drivers
  - ❍ Other (please specify)
- ❒ Decision Making
  - ❍ Familiarity of drivers with the network
  - ❍ Driver aggressiveness
  - ❍ Driver value of time
  - ❍ Compliance
    - – Speed limits
    - – Traffic signals
    - – Ramp metering
    - – Lane restrictions / usage
    - – Route guidance
  - ❍ Road type preference
  - ❍ Other (please specify)
- ❒ Control
  - ❍ Driving skill
  - ❍ Driver impairment
  - ❍ Other (please specify)

1. Does your model represent the traveler characteristic? Please be specific.

2. How do you represent the traveler characteristic in the model? Please be specific – explain both explicit and proxy approaches.

3. How does the characteristic (and corresponding parameters) affect driver behavior?

- ❒ Acceleration ____
- ❒ Lane Changing ____
- ❒ Route choice ____
- ❒ Other (please specify) ____

4. What are the limitations associated with your approach to modeling this vehicle type?

Further comments on simulation of travelers…

Simulation of Traffic Control

I. Traffic Control

Please answer the questions below for each of the following traffic control characteristics:

- ❐ Device property
  - ❍ Type (e.g. ramp meter vs. traffic control)
  - ❍ Size and display (e.g. of the control head, posted sign)
  - ❍ Visibility
  - ❍ Location
  - ❍ Other (please specify) ______________________________
- ❐ Control strategy
  - ❍ Control logic type (e.g. pre-timed, actuated, priority, adaptive)
  - ❍ Cycle length / green time
  - ❍ Other (please specify) ______________________________
- ❐ Surveillance system
  - ❍ Electronic enforcement
  - ❍ Other (please specify) ______________________________
- ❐ Toll collection
  - ❍ Technology type
  - ❍ Processing delay
  - ❍ Other (please specify) ______________________________

6. Does your model contain parameters for the traffic control characteristic? Please be specific.

7. How do you represent the traffic control characteristic in the model? Please be specific – explain both explicit and proxy approaches.

8. How does the characteristic (and corresponding parameters) affect driver behavior?

- ❐ Acceleration ______________________________
- ❐ Lane Changing ______________________________
- ❐ Route choice ______________________________
- ❐ Other (please specify) ______________________________

9. What are the limitations associated with your approach to modeling this characteristic?

Further comments on simulation of incidents…

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