Microscopic Analysis of Traffic Flow in Inclement Weather

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16. Abstract

Weather causes a variety of impacts on the transportation system. An Oak Ridge National Laboratory study estimated the delay experienced by American drivers due to snow, ice, and fog in 1999 at 46 million hours. While severe winter storms, hurricanes, or floodings can result in major stoppages or evacuations of transportation systems and cost millions of dollars, the day-to-day weather events such as rain, fog, snow, and freezing rain can have a serious impact on the mobility and safety of the transportation system users. Despite the documented impacts of adverse weather on transportation, the linkages between inclement weather conditions and traffic flow in existing analysis tools remain tenuous. This is primarily a result of limitations on the data used in research activities.

The scope of this research included use of empirical data, where available, to estimate weather impacts on three categories of submodels related to driver behavior, longitudinal vehicle motion models (acceleration, deceleration and car-following models), lane-changing models and gap acceptance models. Empirical data were used to estimate impacts of adverse weather on longitudinal and gap acceptance models but no suitable datasets were identified for lane-changing models. Existing commercial microsimulation software packages were then reviewed to identify whether and how weather-related factors could be utilized in these models. The various submodels used in these packages to estimate longitudinal motion, lane-changing and gap acceptance models were evaluated. The research found that for the most part, weather-related factors could be incorporated into these models, although the techniques vary by package and by type of model. Additional empirical research is needed to provide confidence in weather-related adjustment factors, particularly as relates to ice and snow. This report concludes with some recommendations of future research related to weather and traffic flow. Additional work is proposed related to human factors and microscopic traffic modeling.

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Weather, traffic flow, statistical models, human factors, microsimulation	No restrictions.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^{o}F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^{o}C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^{o}C	Celsius	1.8C+32	Fahrenheit	^{o}F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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Executive Summary

ES.1 Background

Weather causes a variety of impacts on the transportation system. An Oak Ridge National Laboratory study estimated the delay experienced by American drivers due to snow, ice, and fog in 1999 at 46 million hours (Ref 1). While severe winter storms, hurricanes, or floodings can result in major stoppages or evacuations of transportation systems and cost millions of dollars, the day-to-day weather events such as rain, fog, snow, and freezing rain can have a serious impact on the mobility and safety of the transportation system users. These weather events can result in increased fuel consumption, delay, and crashes, and significantly impact the performance of the transportation system.

Despite the documented impacts of adverse weather on transportation, the linkages between inclement weather conditions and traffic flow in existing analysis tools remain tenuous. This is primarily a result of limitations on the data used in research activities. Research has been limited on the microscopic driving behavior as well, particularly in the areas of vehicle-following and lane-changing. These are critical parameters in understanding the effectiveness of different traffic management strategies. Researchers and practitioners need improved weather data sets and analytical models that can connect traffic flow to specific weather impacts. Over the past few years a number of advances have been made in both macroscopic and microscopic research on the impacts of weather on traffic flow. Expansion of both ITS systems and state DOT-operated RWIS systems is providing greater opportunity to identify the impact of adverse weather on system speeds and incident frequency. Video-based studies of driver behavior are providing another rich source of data in this area. These studies include video of driver behavior at individual intersections or freeway merge locations. Work being conducted under the U.S. DOT's IntelliDrive℠ program is providing another potential data source, which has the potential to provide data on both driver characteristics and weather conditions, collected through vehicle on-board units. Ultimately this work is pointed toward the use of weather-related adjustment factors in advanced traffic management strategies to help reduce weather-related congestion and improve safety.

ES.2 Goals and Objectives

This project represents the second phase of research sponsored by FHWA's Road Weather Management Program (RWMP). The first phase of research was summarized in a report issued in October 2006, *Empirical Studies of Traffic Flow on Inclement Weather*, prepared for FHWA by Cambridge Systematics and Virginia

Tech Transportation Institute. This research was conducted within the goals and objectives set for the RWMP. The overall goal of the research study was to develop a better understanding of the impacts of weather on traffic flow. The research was intended to accomplish the following specific objectives:

1. Study the impact of precipitation on macroscopic traffic flow parameters over a full range of traffic states;
2. Study the impact of precipitation on macroscopic traffic flow parameters using consistent, continuous weather variables;
3. Study the impact of precipitation on macroscopic traffic flow parameters on a wide range of facilities;
4. Study regional differences in reaction to precipitation; and
5. Study macroscopic impacts of reduced visibility (Ref 2).

The first phase of research focused on the use of traffic detector and weather data to estimate changes in traffic flow resulting from adverse weather. The scope of the second phase research included use of empirical data, where available, to estimate weather impacts on three categories of submodels related to driver behavior:

- **Longitudinal Vehicle Motion Models** explain the behavior of forward-moving traffic and include three subsets of models:
    a. Car-following models explain the behavior of drivers in following vehicles traveling behind a lead vehicle. The test hypothesis is that adverse weather will result in more cautious behavior by following vehicles,
    b. Deceleration models explain the behavior of drivers as they decelerate either voluntarily or in response to various events (congestion ahead, weather, incidents), and
    c. Acceleration models explain the behavior of drivers as they accelerate in various situations;
- **Lane-Changing Models** model the conditions under which drivers change lanes; and
- **Gap Acceptance Models** explain the behavior of drivers as they enter a traffic stream or make turns in an intersection against an opposing stream of traffic.

Existing commercial microsimulation software was then reviewed to identify whether and how weather-related factors could be utilized in these models.

ES.3 Research Summary and Conclusions

The work documented in this report consisted of several tasks:

1. Update of literature review conducted in Phase 1;
2. Update of databases available for proposed research;
3. Development of research plan;
4. Research and analysis; and
5. Evaluation of incorporating research results into microsimulation models.

The Literature search identified a large number of recent studies that are documented in Section 2.0 of this report. Potential datasets for analysis were identified through the literature search and through other contacts of the project team. Ultimately about a dozen potential datasets were reviewed, with two being deemed suitable for the proposed analysis in this project. These datasets, from the 100-car study and the CICAS (Cooperative Intersection Collision Avoidance System)-V project are summarized in Table ES.1.

Table ES.1 Summary of Identified Datasets

Study/ Dataset Title	Dataset Characteristics	Size (Terabytes)	Number of Cam Views	Hours of Driving	VMT
100-Car Study	Continuous naturalistic data collected for 241 primary and secondary drivers in the Washington, D.C. area over 12 to 13 months.	6.4	5	43,000	2M
CICAS-V: Live Stop-Controlled Intersection Data Collection	Infrastructure-based study. Measured a variety of state and kinematics information for vehicles at six approaches over five stop-controlled intersections (such as brake status, acceleration, and velocity) over two months each (total data collection period: 16 months).	1.5	4	6,416	N/A

The 100-car study data were proposed for use in the lane-changing analysis but ultimately could not be used due to problems with the data that are documented below. The CICAS-V data were used for all other analyses conducted, including:

- Deceleration Analysis;
- Acceleration Analysis;
- Steady-State Car-Following Modeling; and
- Gap Acceptance Modeling.

Some of the conclusions obtained from the research are listed below:

- With regards to **car-following behavior** the study presented different approaches to modeling car-following behavior. These approaches were compared and the study demonstrated that the Van Aerde (INTEGRATION Model) and Gipps (CORSIM microsimulation model) provide the highest level of flexibility in capturing driver behavior under multiple regimes across different roadway facility types. Procedures for calibrating the steady-state behavior of various car-following models also were developed using macroscopic loop detector data. In order to account for inclement weather effects, adjustment to the steady-state parameters can be achieved using weather adjustment factors.
- The modeling of **vehicle deceleration behavior** is achieved by introducing a maximum deceleration level. In modeling inclement weather conditions, the maximum deceleration level can be modified to account for the reduction in the roadway adhesion conditions. These modifications were developed using the CICAS-V data for all vehicles arriving at the Pepper's Ferry Road/ SR 460 intersection. Alternatively, the modeling of **vehicle acceleration behavior** is achieved through the use of either vehicle kinematics or vehicle dynamics models. The use of a vehicle dynamics model is more appropriate because roadway surface parameters can be directly adjusted within the model.
- **Lane-changing behavior** is usually modeled in three steps: 1) the decision to consider a lane change; 2) the decision to execute a lane change; and 3) the actual execution of the lane change. Item 1 is something that cannot be measured in the field, while Item 2 is modeled using gap-acceptance procedures similar to what was presented on the gap acceptance analysis. The actual execution of lane-changing can be captured using the car-following procedures that were described earlier. No lane-changing data were available to conduct this analysis so that the process described above will need to be tested in a future phase of research.
- **Gap acceptance behavior** is used to model a driver's decision to accept a gap through an opposing flow, in the case of a permissive left turning vehicles at a signalized intersection or vehicles at a two-way stop sign crossing the main street. In addition, gap acceptance procedures are used for the modeling of a driver's decision to make a lane change. The modeling of gap acceptance behavior is achieved through the use of either logit or probit models. Adjustment factors can be included in these models to account for the effect of inclement weather on a driver's gap acceptance behavior.

The CICAS-V data were used to conduct the gap analysis for this project. Gap acceptances were calculated from video taken at the three intersections. Three models were hypothesized and the coefficients in all of the models were determined by fitting the extracted data using a generalized linear regression model. The project team was able to identify a model that could be used to adjust gap acceptance for rainy conditions but no snow conditions were experienced during the data collection period. Figure ES.1 summarizes the models estimated for the impact of rain and waiting time on gap acceptance. The results show that adverse weather does appear to have a significant impact on gap acceptance decisions at intersections.

The last phase of the research included a review of commercial microsimulation packages and specifically the potential for incorporating weather-related factors into the various submodels of these packages. In general, the research found that adjustment factors can be included, but that additional research is required, especially on lane-changing models, before these adjustments can be made with confidence. As indicated in Table ES.2 the various categories of longitudinal motion models can be incorporated into microsimulation software, although within limits in many cases.

Figure ES.1 Effect of Waiting Time and Rain Intensity on Critical Gap Value for Different Models

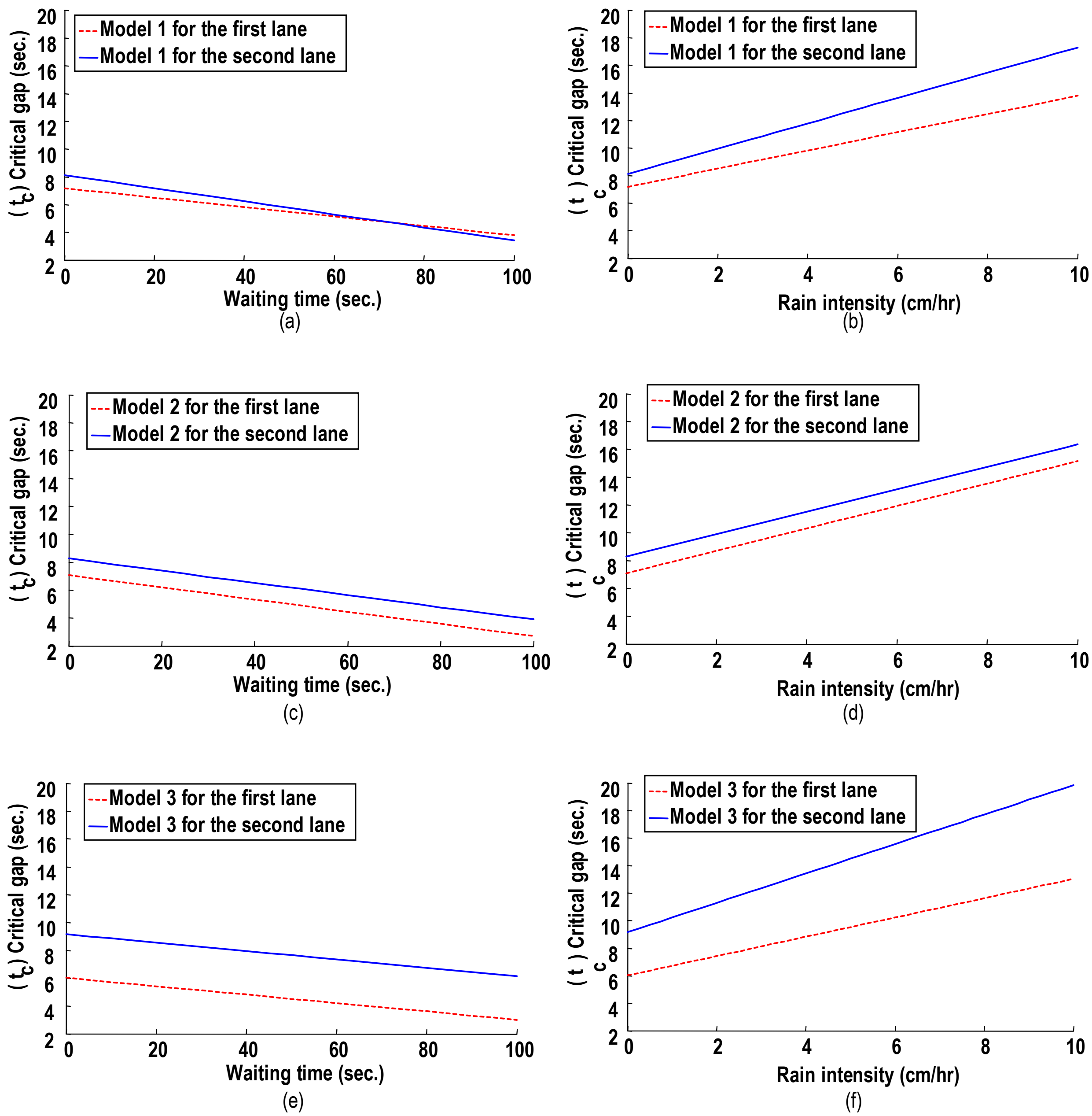


Table ES.2 Feasibility of Incorporating Longitudinal Motion Models into Microsimulation Packages

		Longitudinal Motion		
		Car-Following	**Acceleration**	**Deceleration**
CORSIM	Feasibility	Yes but cannot change speed-at-capacity. Also can only be done for the entire network.	Yes	No
	Data Required	WAFs to compute the free-flow speed and driver sensitivity factor.	Run a vehicle dynamics model first with modified roadway adhesion and rolling resistance coefficients to generate the acceleration versus speed relationship. One major problem is that this is network-specific.	?
VISSIM	Feasibility	Yes but cannot change speed-at-capacity. Also can only be done for the entire network.	Yes	Yes
	Data Required	WAFs to compute the free-flow speed and saturation flow rate. These can then be used to modify the BX and EX parameters or the CC0 and CC1 parameters.	Run a vehicle dynamics model first with modified roadway adhesion and rolling resistance coefficients to generate the acceleration versus speed relationship. One major problem is that this is network-specific.	Use deceleration adjustment factor.
Paramics	Feasibility	Yes but cannot change speed-at-capacity. Also can only be done for the entire network.	Yes	Yes
	Data Required	WAFs to compute the free-flow speed and saturation flow rate. These can then be used to modify the A_0, T_D, and T_r parameters.	Run a vehicle dynamics model first with modified roadway adhesion and rolling resistance coefficients to generate the acceleration versus speed relationship. One major problem is that this is network-specific.	Use deceleration adjustment factor.
AIMSUN2	Feasibility	Yes	Yes	Yes
	Data Required	WAFs used to compute the free-flow speed, saturation flow rate, and speed-at-capacity. These are then used to modify the deceleration rate b) and reaction time (T).	Run a vehicle dynamics model first with modified roadway adhesion and rolling resistance coefficients to generate the acceleration versus speed relationship. One major problem is that this is network-specific.	Use deceleration adjustment factor.
INTEGRATION	Feasibility	Yes. Adjust free-flow speed, speed-at-capacity, and saturation flow rate using weather adjustment factors.	Adjust roadway coefficient of adhesion and rolling resistance coefficients.	No. Currently the deceleration level is fixed. This could easily be changed.
	Data Required	Rain intensity and WAFs.	Coefficient of roadway adhesion and rolling resistance coefficients.	Use deceleration adjustment factor.

Given that the project was not able to gather any data on lane-changing behavior it was not possible to capture the impact of inclement weather on lane-changing behavior at this point. It is the conclusion of the research team that lane-changing behavior can be incorporated into all of the reviewed simulation packages by adjusting the gap acceptance parameters. A summary of how the parameters can be altered and what data are required to do so is provided in Table ES.3.

Table ES.3 Incorporation of Weather-Related Factors into Lane-Changing Models

		Lane Changing
CORSIM	Feasibility	Could not find material on the modeling approach.
	Data Required	–
VISSIM	Feasibility	Yes by adjusting the safety distance adjustment factor and the maximum deceleration level.
	Data Required	Use the steady-state car-following models to adjust the safety distance and the roadway surface condition to adjust the deceleration levels.
Paramics	Feasibility	Could not find material on the modeling approach.
	Data Required	–
AIMSUN2	Feasibility	Yes by adjusting the Visibility Distance and the Maximum Give Way Time Variability.
	Data Required	Data need to be gathered to characterize how the maximum give way time varies as a function of inclement weather.
INTEGRATION	Feasibility	Yes by the lane-change duration and the acceptable gap using the adjusted steady-state car-following model spacing.
	Data Required	Data need to be gathered to characterize how lane change durations vary as a function of inclement weather and how gap acceptance behavior changes as a function of inclement weather.

Table ES.4 summarizes the findings with regard to the incorporation of gap acceptance models into microsimulation packages. PARAMICS could not be evaluated as part of this analysis due to limited documentation. Adjustments are possible in VISSIM, PARAMICS, and AIMSUN2. AIMSUN2 requires calibration of a vehicle dynamics model, while the other two packages can accommodate the type of gap acceptance model developed for this project.

Table ES.4 Incorporation of Weather-Related Factors into Gap Acceptance Models

		Gap Acceptance
CORSIM	Feasibility	By changing the default parameters.
	Data Required	Use the gap models that are being developed to adjust the gap acceptance parameters.
VISSIM	Feasibility	Yes by adjusting the visibility distance, the front gap, rear gap, and safety distance factor.
	Data Required	Use the gap models that are being developed to adjust the gap acceptance parameters.
Paramics	Feasibility	Not reviewed.
	Data Required	–
AIMSUN2	Feasibility	Yes by adjusting the acceleration level, the maximum give way time, and visibility distance.
	Data Required	Adjust the maximum acceleration using a vehicle dynamics model with adjusted wet pavement parameters. It is not clear how the give way time can be adjusted.
INTEGRATION	Feasibility	Yes by adjusting the critical gap size, distribution, and effect of wait time.
	Data Required	Use the gap models that are being developed to adjust the gap acceptance parameters.

ES.4 RECOMMENDED FUTURE WORK

FHWA has identified the following activities for the next phase of research:

- Calibrate the car-following model in various weather conditions using real data – Datasets from research conducted by Hokkaido University in Japan has been identified for this purpose but other datasets may be available as well;
- Develop a gap acceptance model for signalized intersections under snowy conditions – Data will be collected from the CICAS-V intersections used in this study. Alternate locations in areas with higher average snowfall also will be identified;
- Validate the gap acceptance model for signalized intersections under rainy conditions using data from other locations. Additional research is needed to identify alternate locations; and
- Develop procedures for integrating the microscopic models in commercial Traffic Analysis Tools (TAT), including CORSIM and VISSIM.

1.0 Introduction

Macroscopic impacts on traffic flow resulting from adverse weather are the aggregate results of microscopic (individual) driver behavior. Microscopic driver behavior includes acceleration, deceleration, car-following, lane-changing behavior, and gap acceptance. Though macroscopic traffic behavior has been researched and modeled for decades, knowledge of microscopic driving behavior remains limited, mainly because human behavior is so complex and microscopic data collection is expensive. While it is logical to conclude that adverse weather results in a more challenging driving environment, the exact mechanisms for a motorist's response to weather events are limited. Knowing which critical parameters within a driving behavior model should be changed under various weather conditions would aid in the development of weather-responsive traffic management strategies.

This report documents research sponsored by the FHWA Road Weather Management Program. Initial research completed in 2006 involved an analysis of traffic and weather data to develop empirical models that quantify the impacts of weather on traffic flow (Ref 2). Data from three cities – Seattle, Minneapolis, and Baltimore – were used to develop statistical models and adjustment factors for traffic capacity, speed, and density as functions of precipitation intensities and visibility levels. The study also proposed data collection and analysis procedures for microscopic/human factors responses to inclement weather.

This report documents the results of the first phase of the Microscopic Analysis of Traffic Flow in Inclement Weather project. The objectives of the project are: 1) to review and summarize existing research, data, and analytical procedures related to driver behavior on freeways and arterial roads during inclement weather; 2) develop and implement a methodology for identifying and modeling microscopic traffic parameters that are influenced by poor road weather conditions for both freeways and arterials; and 3) recommend procedures for incorporating results of the study into existing traffic microsimulation models, including CORSIM, VISSIM, Paramics, and others.

The report looks at the following categories of submodels:

- **Longitudinal Vehicle Motion Models** explain the behavior of forward-moving traffic and include three subsets of models:
  a. Car-following models explain the behavior of drivers in following vehicles traveling behind a lead vehicle. The test hypothesis is that adverse weather will result in more cautious behavior by following vehicles,
  b. Deceleration models explain the behavior of drivers as they decelerate either voluntarily or in response to various events (congestion ahead, weather, incidents), and
  c. Acceleration models explain the behavior of drivers as they accelerate in various situations;
- **Lane-Changing Models** model the conditions under which drivers change lanes; and
- **Gap Acceptance Models** explain the behavior of drivers as they enter a traffic stream or make turns in an intersection against an opposing stream of traffic.

Section 2.0 summarizes an update of the literature search conducted for this project. Section 3.0 discusses the research methods for this analysis while Section 4.0 includes the results of the research itself, with focus on weather-related adjustment factors. Section 5.0 discusses methods for incorporating weather-related adjustment factors into microsimulation models.

2.0 Literature Review

2.1 Introduction

This section presents the results of a literature review of recent and current research related to driver behavior (i.e., lane-changing, car-following, gap acceptance, turning movements, acceleration and deceleration, etc.) on arterials and freeways in various weather conditions. This review built on the review that was conducted as part of the first phase study.

2.2 Method

The previous study conducted an extensive literature review that documented studies and research related to the impacts of adverse weather on traffic flow. Results were presented for both macroscopic and microscopic research. In addition, a separate human factor category was included that contained studies focusing on driver behavior. These studies frequently involved the use of driving simulators or instrumented vehicle data collection.

Given the previous extensive literature research in this area, the current effort was focused in the following areas:

- Studies after 2006;
- Impact of weather on driver behavior; and
- Lane-changing, gap acceptance, and car-following studies under various weather conditions.

The following literature search methods and data bases were used:

- National Transportation Library – TRIS on Line;
- TRB Annual Meeting Compendium of Papers on CD;
- Internet search engines (Google, and meta search engines); and
- Electronic library resources (e.g., transportation and behavioral science journals).

2.3 Results

The review of the literature generated an initial set of references that were further reviewed for inclusion in this report. Table 2.1 presents a summary of the results of the literature review. The references are presented in chronological order and in many cases the abstracts from the papers are presented. Again, the focus here was to do a focused review of the literature to help in directing the research. Also, the literature presented here will be further summarized in the final report for the project.

Table 2.1 Summary Results of the Review of the Literature

Year	Reference	Authors	Abstract/Summary
2008	Impact of cold and snow on temporal and spatial variations of highway traffic volumes. Journal of Transport Geography Volume 16, Issue 5, Pages 358-372 (In press 2008)	Sandeep Datla, Satish Sharma	Investigation of the impact of cold and snow on daily and hourly traffic volume variations with detailed considerations to the highway type and location. The study results indicate that the impact of cold and snow on traffic volume varies with day of the week, hour of the day, and the type of highway. The commuter roads experience lowest reductions in traffic volume due to cold (up to 14 percent) while the recreational roads experience highest reduction (up to 31 percent). Impact of cold on offpeak hours (10 percent to 15 percent) is generally higher than peak hours (6 percent to 10 percent) for commuter roads and an opposite pattern is observed for recreational roads (peak-hour reductions of 30 percent to 58 percent and offpeak hour reductions of 18 percent to 30 percent). A clear indication of reduction in traffic volume due to snow also is observed for all types of highways.
2008	Modeling impacts of adverse weather conditions on a road network with uncertainties in demand and supply. Transportation Research Part B, vol. 42, n°10, pp 890-910 (2008)	William H.K. Lam, Hu Shao, Agachai Sumalee	This paper proposes a novel traffic assignment model considering uncertainties in both demand and supply sides of a road network. These uncertainties are mainly due to adverse weather conditions with different rainfall intensities on the road network. A generalized link travel time function is proposed to capture these effects. The proposed model allows the risk-averse travelers to consider both an average and uncertainty of the random travel time on each path in their path choice decisions, together with the impacts of weather forecasts. Elastic travel demand is considered explicitly in the model responding to random traffic condition in the network. In addition, the model also considers travelers' perception errors using a logit-based stochastic user equilibrium framework formulated as fixed point problem. A heuristic solution algorithm is proposed for solving the fixed point problem. Numerical examples are presented to illustrate the applications of the proposed model and efficiency of the solution algorithm.
2008	Effects of adverse weather on traffic crashes: systematic review and meta-analysis. TRB 87th Annual Meeting, Washington, D.C.	Lin Qiu and Wilfrid A. Nixon	Studies between 1967 and 2005 that examined the interaction of weather and traffic safety were reviewed. Thirty-four papers and 78 records that meet the predetermined criteria were included in the analysis. The crash rates from each study were normalized with respect to effect size or percent change for meta-analysis generalization. The results indicate that crash rate usually increases during precipitation. Snow has a greater effect than rain on crash occurrence: Snow can increase the crash rate by 84 percent (95 percent confidence interval [CI] =0.68, 0.99), injury rate by 75 percent (95 percent CI = 0.54, 0.96).

Year	Reference	Authors	Abstract/Summary
2008	Association of Highway Traffic Volumes with Cold, Snow, and Their Interactions. TRB 87th Annual Meeting, Washington, D.C.	Sandeep Datla and Satish Sharma	Presented in this paper is the association of highway traffic flow with severity of cold, amount of snow and various combinations of cold and snow intensities by giving detailed consideration to factors such as highway type and location. The study is based on hourly traffic flow data from 350 permanent traffic counter sites located on the provincial highway system of Alberta, Canada, and weather data obtained from Environment Canada weather stations located within 10 miles of the selected permanent traffic counter sites, during the period of 1995 to 2005. Multiple regression analysis is used in the modeling process. The model parameters include three sets of variables: amount of snowfall as a quantitative variable, categorized cold as a dummy variable and an interaction variable formed by the product of the above variables. The developed models closely fit the real data with R-square values greater 0.99. The study results indicate that the association of highway traffic flow with cold and snow varies with day of week, hour of day, and severity of weather conditions. Traffic volume on a day decreases with the increase in severity of cold and snow. A reduction of one percent to two percent in traffic volume for each centimeter snowfall is observed when the mean temperatures are above 0 degrees. For the days with zero precipitation, reductions in traffic volume due to mild and severe cold are 1 percent and 31 percent, respectively. An additional reduction of 0.5 percent to 3 percent per each centimeter of snowfall results when snowfall occurs during severe cold conditions.
2008	Effects of Dry/Compacted Snow Conditions for Passing Behavior by Driving Tests on Rural Highways. TRB 87th Annual Meeting, Washington, D.C.	Munehiro, K.	The study included driving tests on overtaking behavior and on subjective evaluation of safety under dry and compacted-snow conditions on a 2-lane section and on a 2+2-lane section. Ten drivers participated in a test on a road section in service. A vehicle dynamics recorder was installed on a test vehicle that traveled both directions on a 19.0-kilometer test section of a rural highway in Eastern Hokkaido, Japan. Ten male drivers drove the test vehicle under free-flow condition. On the 2+2-lane section, the test vehicle overtook a preceding vehicle. The driving behavior of the overtaking vehicle was recorded using a vehicle dynamics recorder on the rear seat. After each test run, the driver filled in a questionnaire on subjective safety. It was found that the velocity during overtaking is lower for the compacted-snow condition than for the dry condition, and that the variation in longitudinal and transverse acceleration was higher for the compacted-snow condition than for the dry condition. The subjective safety assessment value for the compacted-snow condition was lower than for the dry condition.

Year	Reference	Authors	Abstract/Summary
2008	Inclement Weather Impacts on Freeway Traffic Stream Behavior. TRB 87th Annual Meeting, Washington, D.C.	Rakha, Farzaneh, Arafeh, and Sterzin	The research reported in this paper quantifies the impact of inclement weather (precipitation and visibility) on traffic stream behavior and key traffic stream parameters, including free-flow speed, speed-at-capacity, capacity, and jam density. The analysis is conducted using weather data (precipitation and visibility) and loop detector data (speed, flow, and density) obtained from the Baltimore, Minneapolis/St. Paul, and Seattle areas in the U.S. The precipitation data included intensities up to 1.6 and 0.33 cm/h for rain and water equivalent of snow intensity, respectively. The paper demonstrates that the traffic stream jam density is not affected by weather conditions. Snow results in larger reductions in traffic stream free-flow speed and capacity when compared to rain. Reductions in roadway capacity are not affected by the precipitation intensity except in the case of snow. Reductions in free-flow speed and speed-at-capacity increase as the rain and snow intensities increase. Finally, the paper also develops free-flow speed, speed-at-capacity, and capacity weather adjustment factors that are multiplied by the base clear condition variables to compute inclement weather parameters. These adjustment factors vary as a function of the precipitation type, precipitation intensity, and visibility level. It is intended that these adjustment factors be incorporated in the Highway Capacity Manual.
2008	Assessing the Impact of Weather on Traffic Intensity. TRB 87th Annual Meeting, Washington, D.C.	Mario Cools, Elke Moons, Geert Wets	The main objective of this study was the identification and comparison of weather effects on traffic intensity at different site locations. To assess the impact of weather conditions on traffic intensity, the upstream and downstream traffic of four traffic count locations were considered. The traffic intensity data originate from minute data coming from single inductive loop detectors, collected by the Flemish Traffic Control Center. Data concerning weather events were recorded by the Royal Meteorological Institute of Belgium. The main modeling philosophy envisaged in this study to identify and quantify weather effects is the linear regression approach. Most appealing result of this study for policy-makers, is the heterogeneity of the weather effects between different traffic count locations, and the homogeneity of the weather effects on upstream and downstream traffic at a certain location. The results also indicated that snowfall, rainfall and wind speed have a clear diminishing effect on traffic intensity, while maximum temperature significantly increases traffic intensity. Further generalizations of the findings are possible by studying weather effects on local roads and by shifting the scope towards travel behavior. Simultaneously modeling of weather conditions, traffic intensity rates, collision risk and activity travel behavior is certainly a key challenge for further research.

Year	Reference	Authors	Abstract/Summary
2007	Car-following decisions under three visibility conditions and two speeds tested with a driving simulator. Accident Analysis and Prevention 39 (2007) 106-116.	Kathy L.M. Broughton, Fred Switzer, Don Scott	The present research aimed to reveal factors that govern car following under conditions of reduced visibility. It employed a KQ-Vection high-fidelity driving simulator to measure the behavior of automobile drivers following a lead vehicle at 13.4 m/s (30 mph) or 22.4 m/s (50 mph) under three visibility conditions – clear or one of two densities of simulated fog. At the higher speed, fog conditions separated participants into a group that stayed within visible range of the lead car, even though the headway time violated the NHTSA recommendations for the speed involved, and another group that lagged beyond the visible range. Data were compared to the model of Van Winsum for car-following (The human element in car-following models. Transportation Research Part F 2, 1999). Contrast and image size measurements allowed comparison to a standard contrast sensitivity function and allowed estimation of the just noticeable difference (JND) term in the Van Winsum model.
2007	A Cybernetic Perspective on Car-Following In Fog. Proceedings of the Fourth International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design, 2007. University of Iowa, Iowa City.	Erwin R. Boer, Stéphane Caro, Viola Cavallo	Drivers often drive at a closer time headway (THW) in fog than in clear whether conditions for similar speed ranges (White and Jeffery, 1980). Closer following is generally considered more dangerous. The hypothesis pursued in this paper is that drivers experience a perceptual-motor benefit from driving closer in fog that results in greater (or equivalent) safety and reduced driving demand. A computational car-following model with an experimentally constructed perceptual module is introduced and used to demonstrate that under some conditions, closer following in fog is indeed beneficial because it effectively reduces drivers' perceptual delay by a sufficient amount to improve controllability of the gap so much that the variability in THW reduces more than (or as much as) the adopted decrease in target THW.

Year	Reference	Authors	Abstract/Summary
2007	The Influence of Fog on Motion Discrimination Thresholds in Car-Following. Proceedings of the Fourth International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design, 2007. University of Iowa, Iowa City.	Stéphane Caro, Viola Cavallo, Christian Marendaz, Erwin Boer, Fabrice Vienne	A possible explanation for close following in fog is that it would allow drivers to control headway more precisely by reducing motion perception thresholds. The purpose of our experiments was to determine the motion discrimination thresholds for closing and receding under normal and foggy conditions. An experiment and a pilot study were conducted on a driving simulator in which subjects were presented with a car-following situation. Subjects had to press a button as soon as they detected that the lead vehicle was closing or receding, and their choice response time was recorded. Several visibility conditions were tested corresponding to different contrasts between the lead vehicle outline and the background, ranging from clear weather conditions to foggy conditions in which the vehicle could only be seen by its rear lights. Initial headway and lead vehicle acceleration also were varied. As expected, response times were longest with small accelerations and long headways. There also was an effect of visibility conditions with longer response times when the contrast between the vehicle outline and the background was five percent or less. Moreover, the reduction of response time corresponding to a reduction of headway was greater in fog than in clear conditions, at least in the given range of distances. This suggests that driving closer in fog may have a perceptual-control benefit in terms of a reduction in response times that partially offsets the reduction in time headway. Driving closer also may benefit lateral trajectory control because the lead vehicle is less likely to be lost in fog. (Note there is literature on the effect of fog on the perception of optic flow which has an impact on judgment of own speed. The present research did not focus on fundamental perceptual mechanisms. However, these may be relevant to driver behavior under adverse driving conditions.)
2007	Age-Related Driving Performance: Effect of Fog under Dual-Task Conditions. Proceedings of the Fourth International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design, 2007. University of Iowa, Iowa City	Rui Ni, Julie Kang, and George J. Andersen	The present study investigated the driving performance of older and younger drivers using a dual-task paradigm. Drivers were required to do a car-following task while detecting a signal light change in a light array above the roadway in the driving simulator under different fog conditions. Decreased accuracies and longer response times were recorded for older drivers, compared to younger drivers, especially under dense fog conditions. In addition, older drivers had decreased car-following performance when simultaneously performing the light-detection task. These results suggest that under poor weather conditions (e.g., fog), with reduced visibility, older drivers may have an increased accident risk because of a decreased ability to perform multiple tasks.

Year	Reference	Authors	Abstract/Summary
2007	Video-Based Vehicle Trajectory Data Collection. TRB 86th Annual Meeting, Washington, D.C.	Kovvali, Alexiadis and Zhang	Vehicle trajectory data provide detailed information on microscopic phenomena that can be used for behavioral modeling of car-following, lane-changing, gap acceptance, cooperative driving, etc. Vehicle trajectories also provide detailed data needed for safety research. Usually, vehicle trajectory data are extracted from high-resolution images – either from video or camera-based data collection to develop a holistic dataset of vehicle positions. In recent years, video data collection and subsequent transcription of video data to vehicle trajectories are being attempted by many transportation researchers. While there have been multiple video data collection efforts conducted across the world, there has been little guidance and recommendations on the selection of data platform, data formats and data elements for vehicle trajectory data collection. As part of the Next Generation Simulation (NGSIM) program, the Federal Highway Administration's conducted an initial prototype, and three vehicle trajectory data collection efforts. This paper documents the guidelines developed for the NGSIM data collection efforts for obtaining efficiently transcribed vehicle trajectories.
2007	Effects of weather and weather forecasts on driver behavior. Transportation Research Part F 10 (2007) 288-299.	Markku Kilpelainen, Heikki Summala	This study addressed the effects of adverse weather and traffic weather forecasts on driver behavior in Finland. Drivers answered a questionnaire on perceptions of weather, self-reported driving behavior, pretrip acquisition of weather information, and possible travel plan changes. Data from traffic weather forecasts, automatic traffic counters, and weather measurement stations concerning the same area (and road) also were collected. Drivers who had acquired information also had made more changes to travel plans, but information acquisition did not have an effect on their on-road driving behavior. However, they estimated prevailing risks higher than those who did not acquire weather information. Drivers generally considered the driving conditions better than the forecast, but significantly less so in darkness than in daylight or civil twilight. Drivers reported various kinds of compensatory behavior during adverse conditions, including a 6- to 7-km/h target speed decrement. This corresponded to traffic flow speed measurements. The results suggest that the on-road driving behavior is predominantly affected by the prevailing observable conditions, rather than traffic weather forecasts.
2004	Impact of traveler advisory systems on driving speed: some new evidence. Transportation Research Part C 12 (2004) 57-72.	Linda Ng Boyle, Fred Mannering	This paper explores the effects of driving behavior using in-vehicle and out-of-vehicle traffic advisory information relating to adverse weather and incident conditions. A full-size, fixed-based driving simulator is used to collect data on drivers' speed behavior under four different advisory-information conditions: in vehicle messages, out-of-vehicle messages, both types of messages, and no messages. The findings of this study suggest that while messages are significant in reducing speeds in the area of adverse conditions, drivers tend to compensate for this speed reduction by increasing speeds downstream when such adverse conditions do not exist. As a result, the net safety effects of such message systems are ambiguous.

Year	Reference	Authors	Abstract/Summary
2002	Motorway driver behavior: studies on car-following. Transportation Research Part F 5 (2002) 31-46. (Not included in previous study.)	Mark Brackstone, Beshr Sultan, Mike McDonald	This paper will report findings of an instrumented vehicle study aimed at assessing one element of driver behavior, that of car-following, on UK motorways. The paper (re-) calibrates one of the most successful of such models – the Action Point model – using dynamic time series data acquired from field tests with an instrumented vehicle. Probability distributions for a number of parameters from the Action Point model are produced and a number of modifications made in order to enhance its value for use in traffic flow and simulation models. Lastly typical headways are compared with existing studies in the area, finding that current headways are far lower than believed. The rationale behind the adoption of such short headways is examined.
1999	Speed adjustment of motorway commuter traffic to inclement weather. Transportation Research Part F 2 (1999) 1-14. (Early paper not included in previous report (Ref 2))	Julia B. Edwards	This paper examines traffic behavior in three weather categories: fine, rain, and misty conditions. Weekly spot speed surveys undertaken on the M4 Motorway, south Wales are analyzed. Each survey recorded the speed (mph) of 200 vehicles in the outside lane of the eastbound, dual two-lane carriageway. Manual observations also were made concerning the weather at the time of each survey. For consistency commuter speeds occurring on the same weekday peak hour were recorded for a six-month period (8±9 a.m. Tuesday mornings), thus, effectively controlling many other external factors that might influence vehicle speeds. Hourly traffic flow information was obtained from an automatic traffic counter located at the survey site. Analysis of this not only confirms the peak hour, but also the consistency the commuters' daily travel routine. Speeds in inclement weather are compared with those in fine conditions (the control). This study found a small, but significant reduction in mean speeds in both wet weather and misty conditions, and yet such speed modifications are not sufficient to compensate for the increased hazard posed by inclement weather.

The literature review found significant progress in the development of datasets that could be used to develop, calibrate, and validate microscopic behavioral relationships (Ref 3). A significant amount of this work also is being performed under the FHWA's Next Generation Simulation (NGSIM) program. However, while the data collected for the NGSIM program improve the ability to estimate car-following, gap acceptance and lane-changing models, the data were collected primarily under fair or nonadverse weather conditions. Additional data also are needed under varying adverse weather conditions.

The research related to macroscopic driver behavior and decision-making was generally consistent with the review. Simulation studies continue to use fidelity driving simulators and laboratory type of methods. These types of procedures and methods have been valuable in examining such areas as decision-making and perceptual factors. However, when using a driving simulator one needs to simulate the driving environment, the vehicle, and the vehicle-environment interactions. The literature search confirmed that there are still a limited number of studies and datasets available that allow a robust microscopic analysis of driver behavior in adverse weather conditions. However, it also provides promise that the continuing deployment of ITS technology and Environmental Sensor Stations, along with a growing number of studies that involve observation of individual drivers, will change this situation.

3.0 Selection of Data for Analysis

3.1 INTRODUCTION

Section 2.0 identified available and potential sources of traffic and weather data that could be used to analyze driver behavior in inclement weather. The data sources were described with respect to the quality, coverage, and appropriateness of the data to support the analysis under this project. Also, the level of effort and cost associated with obtaining, collecting and processing the information for use in this study were considered.

This section describes methods and tools that could be used to analyze the data to support the development of models of driver behavior in inclement weather.

3.2 METHOD

The macroscopic research documented by Hranac et al. (2006) included a review of available data with potential use in studying the effects of adverse weather on driver behavior. The effects of adverse weather on traffic were examined by employing data from freeway traffic detectors and National Weather Service Automated Surface Observing System (ASOS). ASOS data are available for most of the larger airports in the U.S. Data from three cities were used; Baltimore, Seattle and Minneapolis-St. Paul (Ref 1).

The research on microscopic driver behavior involved calibration of specific microscopic submodels, including those for car-following, gap acceptance, and lane changing. The approach identified databases and procedures that could be used to support analysis under this effort. Over the past few years there has been an increase in the use of instrumented vehicles in which detailed driver/vehicle behavior and video data are recorded. Many of these studies tend to focus on examining ITS technologies (e.g., automated cruise control, crash avoidance systems, etc.) and their impact on safety. The 100-Car Study by VTTI is the first large-scale instrumented-vehicle study undertaken with the primary purpose of collecting precrash and near-crash naturalistic driving data. The 100-Car Study is basically collecting driver and vehicle data during "normal" driving conditions.

The macroscopic research documented a major effort to collect detailed vehicle trajectory data to support the development and validation of simulation models (Next Generation Simulation or NGSIM). The NGSIM effort collected data only during clear weather conditions and thus is a useful database for developing and calibrating fundamental algorithms to include in simulation models. It does not, however, support analysis of the effects of adverse weather on driving behavior.

The macroscopic research also identified the IntelliDrive^{SM} program (formerly Vehicle Infrastructure Integration (VII)) as potential source of data. In principle the IntelliDrive^{SM} effort could provide data to support analysis on the effects of adverse weather on driving behavior. However, it appears at the moment that an IntelliDrive^{SM} program component that would provide the needed data will not be available for some time.

The next section documents the full range of datasets that were considered for the second phase research.

3.3 Results

Table 3.1 presents a summary of the data sources that were examined for potential use in this study. Our approach was to first identify sources of traffic and driver behavior data and to examine the data for suitability. A key consideration in determining which datasets were viable for analysis was the availability of appropriate data during adverse weather conditions. Other criteria used are documented in Table 3.1 and include dataset characteristics, size, availability of video, hours of driving and VMT. In the case where the data appeared suitable for the analysis, then availability of corresponding weather data was examined.

As discussed earlier the NGSIM study was not considered for this effort since data were only collected during clear weather days. Also, several of the studies and data sources listed in Table 3.1 are for commercial vehicles only and thus too limited for this study. Several other studies were not far enough along to have data available for this effort.

Table 3.1 includes two recent studies in the area of crash avoidance. These studies were well designed for the questions that they were examining. However, they do not support this research effort as they present very little exposure data that can be used to examine the effect of adverse weather on driver behavior.

The two most promising data sources that were readily available and to which the research team had full and ready access were the 100-Car study and the CICAS-V study.

Table 3.1 Summary of Studies and Databases

Study/Dataset Title	Dataset characteristics	Size (TB)	Number of Cam Views	Hours of Driving	VMT
100-Car Study	Continuous naturalistic data collected for 241 primary and secondary drivers in the Washington, D.C. area over 12 to 13 months. (Completed 2006)	6.4	5	43,000	2 M
DDWS FOT	Continuous data collected from 103 nighttime truck drivers, each for a 12- to 13-month period (total data collection period: 18 months). Measures collected include driver input and performance, sleep quantity and quality, video, and questionnaires. (Completed 2005)	11.8	4	46,000	2.3 M
Impact of Local/Short-Haul Operations on Driver Fatigue	Field study portion collected continuous naturalistic data from 42 short-haul drivers, each for one work week. (Completed 2005)	N/A	5	1,000	28,000
Investigating Critical Incidents, Driver Restart Period, Sleep Quantity, and Crash Countermeasures in Commercial Vehicle Operations Using Naturalistic Data Collection	94 participants, 8 trucks				
40-Teen Driving Study[a]	Currently in Progress, 40 newly licensed drivers. (Completed 2008)	7	4	19,125	670,000
Older Driver Study[a]	Currently in progress	2.5	4	4,867	131,400
CICAS-V: Live Stop-Controlled Intersection Data Collection	Infrastructure-based study. Measured a variety of state and kinematic information for vehicles at six approaches over five stop-controlled intersections (such as brake status, acceleration, and velocity) over 2 months each (total data collection period: 16 months). (Completed 2007)	1.5	1-2	6,416	N/A
Road Departure Crash Warning (RDCW) System Field Operational Test	RDCW FOT was designed to gain insight into the suitability of road departure crash warning systems for widespread deployment within the U.S. passenger vehicle fleet. A field study was conducted where 78 drivers used the system, each for approximately four weeks (one-week baseline and three weeks with the crash warning system turned on). (Completed 2006)	0.35 (about 350 GB)	2	2,500	133,000 km[a]

Study/Dataset Title	Dataset characteristics	Size (TB)	Number of Cam Views	Hours of Driving	VMT
Automotive Collision Avoidance System field operational test (or ACAS FOT)	Evaluation of the Automotive Collision Avoidance System (ACAS). The ACAS integrates forward collision warning (FCW) and adaptive cruise control (ACC) functions for light-vehicle applications. The ACAS FOT that employed 11 vehicles using a total of 66 drivers. (Completed 2005)	0.35 (about 350 GB)	2	?	130,000 km[b]

[a] Note for the RDCW study approximately 37,600 kilometers were driven without the RDCW turned on. So for the current study only 37,600 kilometers would have been of use.

[b] Approximately 40 percent of the data may not be usable for the present study since the ACC or FCW was activated for about this proportion of the time.

The 100-car study involved 241 drivers over a 12-month driving period in the Northern Virginia and Washington, D.C. areas. There were data on approximately 2,000,000 miles and 42,300 hours of driving. As previously discussed, the vehicles were instrumented and detailed driver/vehicle data were captured along with video data of the driver and the roadway.

The CICAS-V study presents a large database for driver behavior at intersections and for longitudinal driver behavior. The CICAS database includes vehicle performance measures, video recording, and weather data collected at the intersections using Environmental Sensor Stations.

3.4 Dataset Selection and Evaluation

The above two data sets were selected based on their ability to support evaluation of driver behavior at a microscopic level. Also the extent of the data collection efforts (over 12 months of data collection) provided the opportunity for investigating driving behavior under different weather conditions for the same roadway.

Weather data for the CICAS data set were available from the ESS installed at the intersections. Using weather data from the exact location where traffic data are being collected provides a major advantage over other studies in which weather data were collected from locations more remote from the traffic data. For the 100-car study the best source of weather data were from the Meteorological Assimilation Data Ingest System (MADIS). Also, weather data were obtained from the NOAA National Climatic Weather Data Center. The data received were for the Northern Virginia area and provided at one-hour samples.

Evaluation of these data sources revealed some limitations. The identified traffic and driver behavior data were not collected for the purpose of examining the effects of weather on driver behavior. Also, the above sources of identified data are from Northern Virginia and the Blacksburg Virginia areas. Both of these areas have low average annual snowfall and often experience winters with little or no snow.

The analysis of the CICAS-V and the 100-Car data was conducted through the use of the Data Analysis and Reduction Tool (DART). DART is a custom built software that was developed at the Virginia Tech Transportation Institute (VTTI) for synchronizing video and kinematic data. The DART software is integrated with SQL Server 2005 and all data are stored in SQL databases. Users can code different filters to extract subsets of the dataset. In extracting data for the analysis of inclement weather impacts on driver behavior, custom built Matlab (Matrix Laboratory) software will be developed to extract and analyze the data. Matlab has a database toolbox that integrates with SQL server.

3.5 SUMMARY

The identified data sources present the potential for advancing the state of knowledge with respect to the effect of adverse weather on driving behavior. The focus was to identify potential data sources that had a good chance of providing useful data for analysis within time and cost constraints.

Based on our review of available data sources and previous work in this area (e.g., Rakha et al, 2008) the 100-Car and CICAS-V datasets presented the best opportunities for providing additional insight to the problem within the scope of this project.

4.0 Implementation Plan and Methods

4.1 Introduction and Background

The rapid development of personal computers over the last few decades has provided the necessary computing power for advanced traffic microsimulators. Today, microscopic traffic simulation software are widely accepted and applied in all branches of transportation engineering as an efficient and cost-effective analysis tool. One of the main reasons for this popularity is the ability of microscopic traffic simulation software to reflect the dynamic nature of the transportation system in a stochastic fashion.

The core of microscopic traffic simulation software includes car-following, lane-changing, and gap acceptance models. Each of these models are described in this document. The goal of this section is to provide an overview of the modeling procedures of state-of-the-practice traffic simulation software and to propose a modeling approach that could capture the effect of inclement weather.

4.2 Review of Applicable Microscopic Traffic Models and Software

4.2.1 Traffic Simulation Car-Following Models

The modeling of car-following and traffic stream behavior requires a mathematical representation that captures the most important features of the actual behavior. In this treatment, the relationships obtained by observation, experimentation, and reasoning are given: the researcher attempts to express their steady-state behavior in a graphical form, and classify them based on their steady-state representation.

Typically, car-following models characterize the behavior of a following vehicle (vehicle *n*) that follows a lead vehicle (vehicle *n-1*). This can be presented by either characterizing the relationship between a vehicles' desired speed and the vehicle spacing (speed formulation), or alternatively by describing the relationship between the vehicle's acceleration and speed differential between the lead and following vehicles (acceleration formulation).

Over the last few decades, several car-following models have been developed and incorporated within microsimulation software packages. This section describes the characteristics of six of the state-of-practice and state-of-art car-following models, including the Pitt model (CORSIM), Gipps' model (AIMSUN2), Wiedemann74 and 99 models (VISSIM), Fritzsche's model (PARAMICS), and the Van Aerde model (INTEGRATION). Subsequently in this report, each model is characterized based on its steady-state behavior and procedures are developed to calibrate the model parameters.

4.2.2 Lane-Changing Modeling

Different types of model are used to describe lane-changing models. These models can be categorized as: 1) simulation models; 2) mathematical models; and 3) empirical models. These models are described in this section.

Lane-Changing Simulation Models

A lane-changing model is a microscopic algorithm in which individual vehicle maneuvers are considered in a microsimulation software. The model represents the behavior of the system and the changes over time. A typical simulation model of a traffic facility is usually provided with data, including parameters such as drivers' reaction times and desired speeds.

Lane-Changing Mathematical Models

Lane-changing mathematical models often employ statistical techniques to define the probability of a particular event taking place or to represent a set of traffic characteristics by a theoretical distribution. Because of the complexity of traffic behavior, most mathematical models include a number of simplifying assumptions.

Lane-Changing Empirical Models

Empirical models typically take the form of an equation in which the variable predicted, the dependant variable, is expressed as a function of a number of independent variables. The equation is usually derived by regression techniques and is based on observed data. Initially the independent variables that improve the fit of the model need to be identified. This process requires a substantial amount of data covering an appropriate range of facilities and independent variables.

The lane-changing analysis conducted for this project was theoretical, due to the lack of usable data.

4.2.3 Gap Acceptance Modeling

Gap acceptance is a process that occurs when a traffic stream (known as the opposed flow) has to cross another traffic stream (known as the opposing flow) or merge with the opposing flow. Gap acceptance behavior occurs when: 1) vehicles on a minor approach need to cross a major street at a two-way stop-controlled intersection, 2) vehicles have to make a left turn through an opposing through movement at a signalized intersection, 3) vehicles approaching a roundabout have to merge with vehicles traveling in the roundabout, or 4) vehicles merging onto a freeway have to find gaps in the freeway flow. Generally gap acceptance analysis can be divided into two types: 1) crossing gap acceptance at intersections; or 2) gap acceptance during merging or lane-change maneuvers. This report describes both approaches to modeling gap acceptance with a focus on the crossing gap acceptance modeling.

4.3 Description of Data Sources (Traffic and Weather)

Table 4.1 presents a summary of the two data sources that were selected for use in this study. These two data sources are briefly described in this section. As stated in Section 3.0, the two datasets were compiled using the Data Analysis and Reduction Tool (DART). DART is a custom-built software that was developed at VTTI for synchronizing video and kinematics data. The DART software is integrated with SQL Server 2005 and all data are stored in SQL databases that have the same data structure regardless of the study application. Within DART, users can code different filters and robots to extract subsets of the dataset. To facilitate the data analysis, custom Matlab codes will be developed to extract vehicle trajectory data to conduct the analysis.

Table 4.1 Summary of Identified Datasets

Study/Dataset Title	Dataset Characteristics	Size (Terabytes)	Number of Cam Views	Hours of Driving	VMT
100-Car Study	Continuous naturalistic data collected for 241 primary and secondary drivers in the Washington, D.C. area over 12 to 13 months.	6.4	5	43,000	2M
CICAS-V: Live Stop-Controlled Intersection Data Collection	Infrastructure-based study. Measured a variety of state and kinematics information for vehicles at six approaches over five stop-controlled intersections (such as brake status, acceleration, and velocity) over two months each (total data collection period: 16 months).	1.5	4	6,416	N/A

The 100-car study data were proposed for use in the lane-changing analysis but ultimately could not be used due to problems with the data that are documented below. The CICAS-V data were used for all other analyses conducted, including:

- Deceleration Analysis;
- Acceleration Analysis;

- Steady-State Car-Following Modeling; and
- Gap Acceptance Modeling.

100-Car Study Dataset

The 100-Car Study was the first instrumented-vehicle study undertaken with the primary purpose of collecting large-scale naturalistic driving data. Drivers were given no special instructions, no experimenter was present, and the data collection instrumentation was unobtrusive. In addition, the majority of the drivers drove their own vehicles (78 out of 100 vehicles). The dataset contains data at 10 Hz for many extreme cases of driving behavior and performance, including severe drowsiness, impairment, judgment error, risk taking, willingness to engage in secondary tasks, aggressive driving, and traffic violation.

The data collection effort resulted in the following dataset contents: 1) approximately two million VMT; 2) almost 43,000 hours of data; 3) 241 primary and secondary driver participants; 4) 12- to 13-month data collection period for each vehicle, 18-month total data collection period; 5) 15 police-reported crashes; 6) 67 nonpolice-reported crashes (some producing no damage); 7) 761 near-crashes; 8) 8,295 incidents; and 9) 5 channels of video and many vehicle state and kinematics variables.

An "event" database was created, similar in classification structure to an epidemiological crash database, but with video and electronic driver and vehicle performance data appended to it. The events in this case are crashes, near-crashes, and other "incidents" that represent less severe conflicts. These data allow the classification of the following: 1) pre-event maneuver; 2) precipitating factor; 3) event type; 4) contributing factors; 5) associative factors; and 6) avoidance maneuver. Because of the five camera views were used in the 100-Car Study, these data elements include items both within and outside the vehicle.

CICAS-V Dataset

The CICAS-V field study included an infrastructure-based radar and video data collection system that measured a variety of state and kinematics information (such as brake status, acceleration, and velocity) for vehicles at five stop-controlled and three four-way signalized intersections. Data were gathered over two months at each signalized intersection.

The three signalized intersections include:

1. The intersection of Peppers Ferry Road (VA 114) and North Franklin Street (Business Route 460): The Peppers Ferry intersection approach has a 35 mph posted speed limit in both the westbound and eastbound directions. On Franklin Road there is a 45 mph posted speed limit in both the northbound and southbound directions. The entering Average Annual Daily Traffic

(AADT) for this intersection is 31,905 vehicles per day and there have been an average of 23 accidents per year reported at this intersection. This intersection is in proximity to other signalized intersections and thus can be used to characterize driver behavior within a coordinated traffic signal system. (See Figure 4.1.)

Figure 4.1 Aerial View of Peppers Ferry (VA 114) and Franklin (Bus 460) Intersection

Source: Google Earth.

2. Intersection of North Franklin Street (Business Route 460), Elm Street, and Independence Boulevard: The posted speed limits for Franklin Street, Independence Boulevard, and Elm Street are 45 mph, 35 mph, and 25 mph, respectively. VDOT records show the entering AADT at 25,975 vehicles per day. There has been an average of 21 annual crashes reported at this intersection. This intersection is located away from other intersections and thus can serve as an isolated intersection site. (See Figure 4.2.)

3. The intersection of North Franklin Street (Business Route 460) and Depot Street: The Franklin Street eastbound intersection approach has a 35 mph posted speed limit while the westbound intersection approach has a 25 mph posted speed limit. The Depot Street intersection approach has a 25 mph posted speed limit going southbound and a 35 mph posted speed limit going northbound. The entering AADT for this intersection is 26,671 vehicles per day and there was an average of 11 accidents per year reported at this intersection. (See Figure 4.3.)

Figure 4.2 Aerial View of Depot and Franklin Intersection

Source: Google Earth.

Figure 4.3 Aerial View Franklin, Elm, and Independence Intersection

Source: Google Earth.

For CICAS-V, data were collected and analyzed with the goal of understanding how drivers approach intersections under various approach speeds and environmental conditions. The data acquisition system (DAS) employed a suite of hardware and software to record information about vehicles that approached the test sites. The DASs consisted of three major subsystems: 1) sensing network; 2) processing stack; and 3) associated hardware enclosures and mounts.

The sensing network was a distributed subsystem of components that provided raw inputs to the processing stack at a rate of 20 Hz. The sensor suite consisted of the following:

1. **Radar to provide parametric vehicle speed data.** A single radar was mounted on each of the four mast arms below the camera and aimed directly at the approaching traffic. Each radar tracked a total of 64 vehicles as they approached the intersection.
2. **Video cameras to collect the visual scene.** A video camera was installed on each of the four traffic signal mast arms to provide an image of the entire intersection environment.
3. **Weather stations.** The weather station provided weather information once each minute. The collected weather data included long-term rainfall, daily rainfall, wind direction, wind speed, average wind speed, temperature, barometric pressure, and humidity.
4. **Signal phase sniffer provided the signal phase and timing information at each signalized intersection.** The signal sniffer was a custom digital signal processor developed at VTTI. This board uses inductive loops to measure the electrical current flowing to the traffic signal heads. Using the loops, the sniffer monitors the current phase of every signal at the intersection. This method results in a completely unobtrusive system for monitoring the signal phase and timing. It does not require any direct connections to the signal controller; the intersection was never removed from service during installation. In addition, the sniffer learned the yellow phase lengths at the intersection. This learning process took place over the first few phase cycles, after which the sniffer provides a countdown of remaining yellow time until red.
5. **GPS units provided synchronized global time.** A basic GPS system was employed at each intersection primarily for acquiring an accurate global time. This time information is used to stamp the data to enable analysis related to time of day, day of week, etc.

The processing stack preprocessed the sensor data and assembled the dataset in real time while archiving to binary data and compressed video files. As part of this research effort, custom built Matlab codes were developed to extract subsets of data for analysis purposes, as described in the following subsection.

4.3.1 Data Analysis Procedures

From the various datasets, data elements that need to be considered include video and vehicle kinematics data, in-vehicle and surrounding environment data, vehicle- and infrastructure-based data, and raw and reduced data. Processing and analyzing the data requires addressing data storage issues, data storage configuration, reduction capabilities, and the computing requirements necessary to simplify each dataset. The methods used to process and analyze the two datasets are described in this section.

Filtering techniques and triggers were used to extract classification parameters from the selected datasets (e.g., deceleration levels, distance from an intersection, weather condition, etc.). Data storage space, data storage configuration, data reduction capabilities, and computing requirements are integrated issues that vary widely for each analysis. The data storage required for each database depends upon the type and size of data that are available and needed for each analysis. For example, the 100-Car Study raw dataset, including both video and vehicle kinematics data, requires seven terabytes of data storage; however, various reduced datasets may require very little data storage capacity. Depending on the analyses, the smaller datasets may be sufficient, making the requirements for data storage and processing considerably less. When the reduced datasets are used instead of the complete datasets, the data reduction needs are simplified. Nonetheless, video data reduction capability will be an important processing requirement.

The computing requirements necessary for data manipulation and analysis are a result of the data size, data storage configuration, reduction needs, and analysis requirements. Obviously, this can become more complicated when working across databases (e.g., traffic and weather data). The creation of new datasets from existing datasets results in increased storage and computer processing needs. Similarly, the timeframe required to complete one analysis or complete multiple analyses using the same resources can affect the method for processing data since computing power required for one analysis can downgrade the computer system performance so much that other analyses cannot be conducted simultaneously, thereby requiring more computing processing power or more time.

Some problems were identified in some of the datasets. First in the case of the 100-car dataset the following problems were identified:

1. The timestamps in the data were based on the in-vehicle computers and can be off by up to four hours. This problem with the data makes the time matching of vehicle with weather data impossible. However, the video data could be used to identify weather conditions.
2. Only data for the subject vehicle and up to seven targets are included. This made the data unusable or of limited use for the characterization of gap-acceptance and lane-changing behavior.

In the case of the CICAS-V dataset, the data were stored in different files; each file included a single hour of data with a unique File ID. The data were collected at a frequency of 20 Hz (once every one-twentieth of a second) and included the following data:

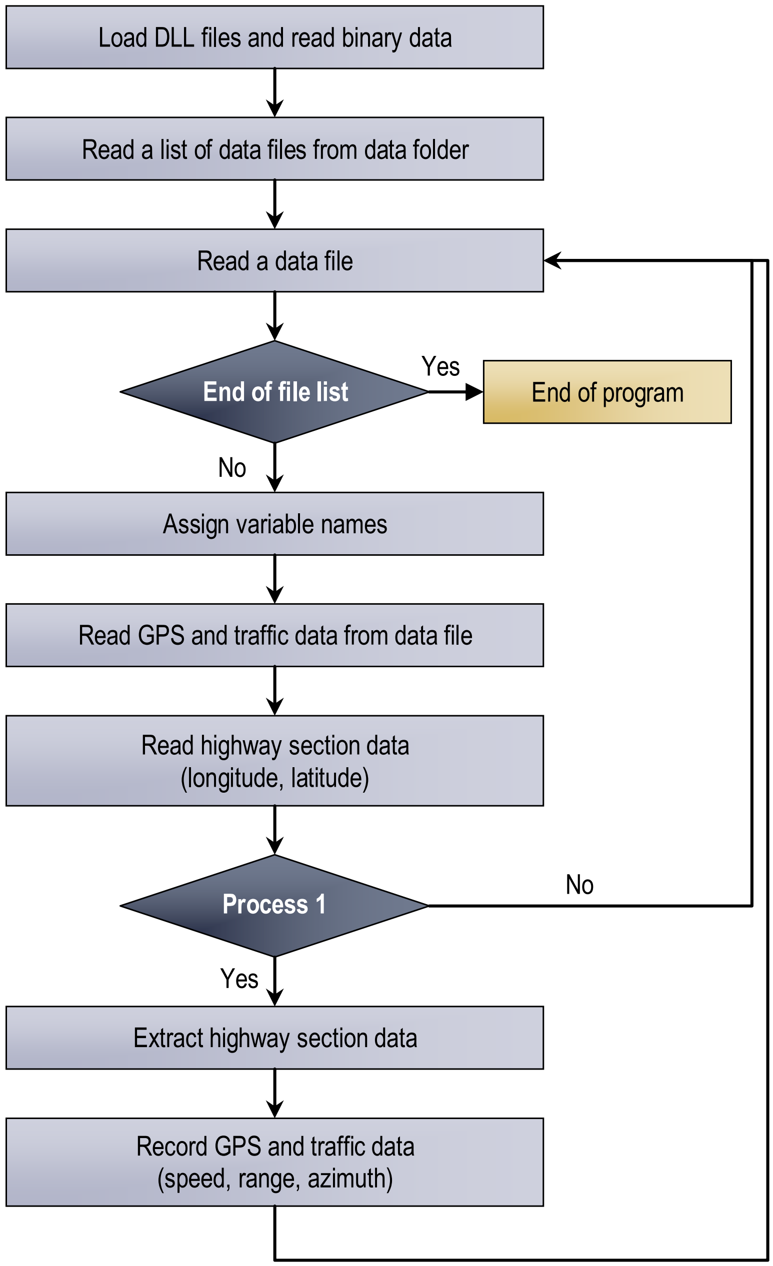
1. **GPSDateTime –** This variable provides the GPS time in yyyy-mm-dd hh:mm:ss.000 format.
2. **FrameNumber –** This variable provides the sync number used to synchronize video with kinematic numerical data (each sync is one-twentieth of a second).
3. **WeatherRain –** This variable provides the accumulated rain fall for each day (millimeters).
4. **WeatherMinuteofDay –** This variable identifies the minute in each day for which weather data are reported. A day is comprised of 1,440 minutes (entries). Each file is comprised of 60 entries.
5. **Range –** This variable provides the distance of the vehicle from the approach stop line (m). The variable is positive when the vehicle is upstream the stop line and negative when it is downstream the stop line.
6. **Velocity –** This variable is recorded for each of the possible 64 vehicle targets (m/s).
7. **Acceleration –** This variable is recorded, but was found to not be accurate. Consequently, the vehicle acceleration was computed from the velocity measurements (m/s^2).
8. **LaneID –** This variable provides unique IDs to each lane/approach combination.

Some of the limitations of the CICAS-V data are:

- They only include data for vehicles within 100 meters of the intersection. This limited use for the characterization of lane-changing behavior.
- The behavior of the vehicle inside the intersection is not captured. This was an issue for the characterization of driver acceleration behavior.
- The data only included two approaches with permissive left turns for the use in the characterization of gap acceptance behavior.

A flowchart of a sample Matlab function that extracts a subset data on a defined highway section is illustrated in Figure 4.4.

Figure 4.4 Sample Flowchart of a Matlab Function



Process 1 –

- Check if test vehicles travel the highway study section based on GPS data
- Check the heading of test vehicle and direction of trip
- Match the distance of study section and the distance that the test vehicle traveled

The use of raw data versus reduced data presents different challenges when extrapolated from one study to another. When reviewing raw data one must consider several issues, including but not limited to:

- The precision of the instrumentation used to collect the data;
- The correctness of the instrumentation installation;
- Spurious data signals that may come from the instrumentation;
- The rate of data collection for the purpose of other analyses; and
- The accuracy of calculated data in the raw data stream.

In some cases, the data element may not be accurate, but it may be easily transformed. An example of such a case is when an accelerometer box is installed backwards in a vehicle. In this case the data can be quickly converted through a simple mathematical procedure without compromising the data integrity.

The use of reduced data presents different challenges that depend on several factors. For example, when reviewing reduced radar data to determine following distance, one must consider the type of radar used, the rate of data collection, how "noisy" the data are, the assumptions used to mathematically smooth the data, and how the smoothing process was verified, among other things. In reviewing reduced video data, one would need to consider the data rate at which the video was collected, who reduced the data (two highly qualified individuals who knew the data in detail versus lower-level recruits), the process used for training reductionists, the intra- and inter-rater reliability, and to what level of accuracy the video and other data were synchronized, among other issues. Of course, this must be determined for each category of variable and for each study accessing the same database.

4.3.2 Risks and Problems

Some of the risks that the team identified based on its analysis of the naturalistic driving data are discussed below together with some solutions developed to address these problems.

Risk/Problem

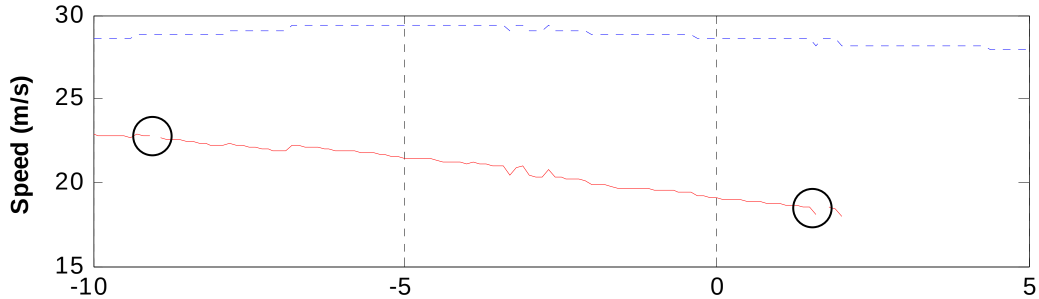
Data (speed and range) may be missing for a few milliseconds while the valid target is being tracked.

Suggested Solution

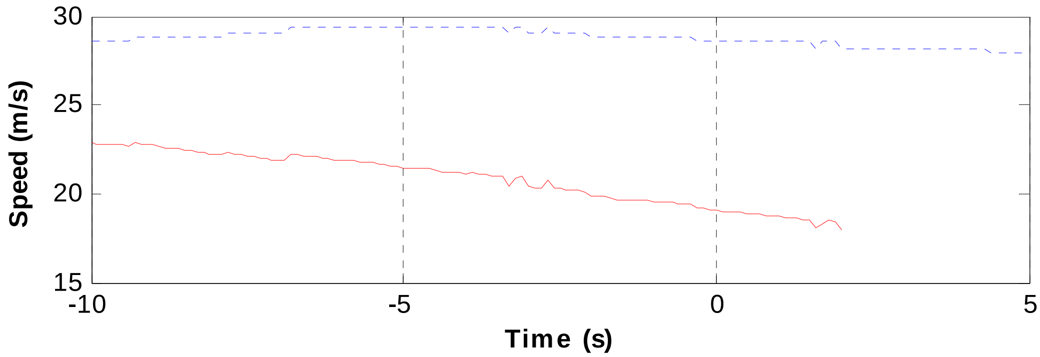
In order to impute missing data a linear interpolation may be performed. Figure 4.5 shows a speed profile with missing values for a target (upper part) and the same profile after performing a linear interpolation (the lower part of the figure).

Figure 4.5 Speed Profile

(a) With Missing Data



b) After Performing Linear Interpolation



Risk/Problem

The Eaton VORAD system used in the 100-car FOT and other naturalistic driver behavior studies simultaneously tracks up to seven targets that change over time.

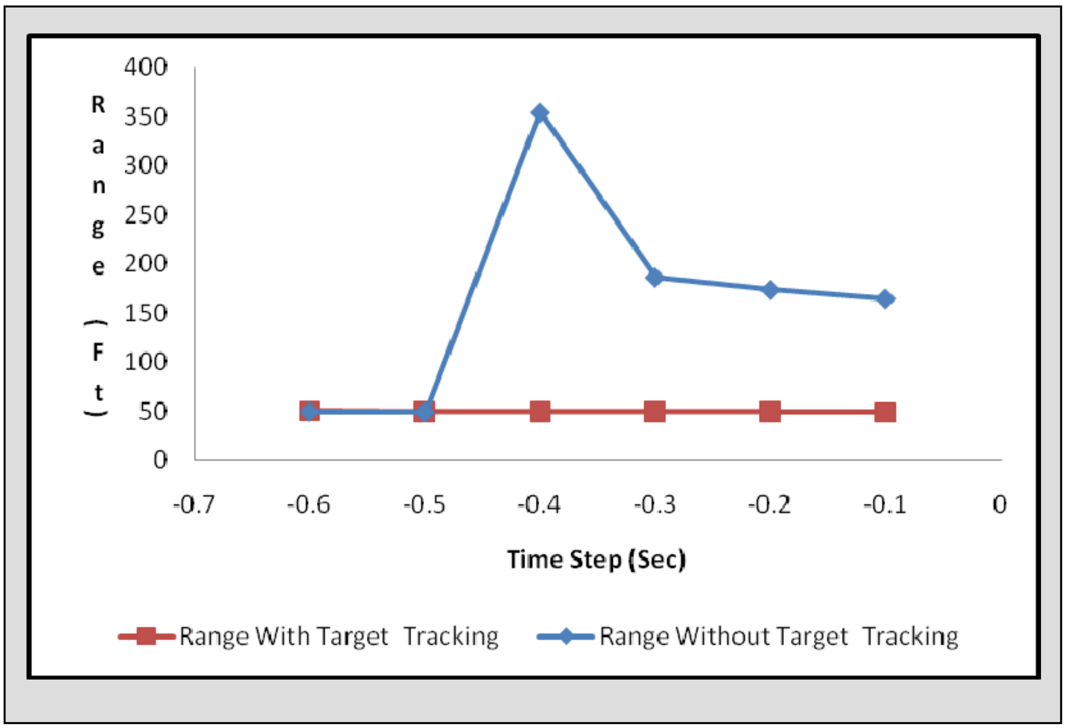
Suggested Solution

VTTI has developed algorithms that identify and track the primary target of interest within the VORAD data. To illustrate the importance of implementing such algorithms, consider the primary target of interest to be Target 231, as shown in Table 4.2. Before implementing the tracking algorithm, i.e., using range values in the "VORAD1_Range_1" range calculations would result in erroneous variable computations, as shown in Figure 4.6. After applying the algorithm correct variables are identified.

Table 4.2 Example Illustration of Radar Target Tracking

	VORAD_ID			VORAD1_Range (Feet)		
Time Step_(sec)	1	2	3	1	2	3
-0.6	231	248	247	50.1	370.1	212.2
-0.5	231	248	247	49.5	363.4	205.8
-0.4	248	231	247	354.5	49.6	193.1
-0.3	247	231	248	186.7	49.6	344.5
-0.2	247	248	231	173.9	331.8	49.5
-0.1	247	231	248	165	49.3	321.8

Figure 4.6 Range with and without Target Tracking



Risk/Problem

Presence of invalid readings or null values. For example, as part of VTTI's analysis of the CICAS-V data, rain gauge measurements were recorded every 20 Hz. In examining the rain gauge data, invalid (unrealistic) measurements were found as shown in Table 4.3 (196.088 mm). In addition, Table 4.4 shows another example of unrealistic data. In this case the GPS time reports a null value for one of the entries.

Table 4.3 Rain Gauge Measurements

Rain Gauge Measurements (Invalid Values), mm	Rain Gauge Measurements (Corrected) mm
8.382	8.382
196.088	8.382
196.088	8.382
196.088	8.382
196.088	8.382
8.382	8.382
8.382	8.382

Suggested Solution

An algorithm was developed to identify such unusual rainfall values and replace them with the average of the before and after values in the case of the first problem. In the case of the second problem, algorithms were developed to replace invalid or missing data, as demonstrated in Table 4.4.

Table 4.4 GPS Imported Data (Null Values)

GPSDateTime (with Null Values)	GPSDateTime (Corrected)
'2007-06-22 06:30:39.617'	'2007-06-22 06:30:39.617'
'2007-06-22 06:30:39.617'	'2007-06-22 06:30:39.617'
Null	'2007-06-22 06:30:39.617'
'2007-06-22 06:30:39.617'	'2007-06-22 06:30:39.617'
'2007-06-22 06:30:39.617'	'2007-06-22 06:30:39.617'
'2007-06-22 06:30:39.903'	'2007-06-22 06:30:39.903'

Risk/Problem

Weather station calibration of time setting. In this example, the variable Rain_Today field, which records the cumulative rainfall since 12:00 a.m., is reset back to zero. Unfortunately, the controller times do not necessarily coincide with the local time and thus the resetting has to be done at 13:29 according to the local time (shown as 17:29 UTC in Table 4.5).

Table 4.5 Weather Station Input Data

Row number	GPS	Minute of Day	Rain_Today
57809	'2007-04-26 17:29:38.367'	1,439	8.382
57810	'2007-04-26 17:29:38.367'	1,439	8.382
57811	'2007-04-26 17:29:38.367'	0	0
57812	2007-04-26 17:29:38.367	0	0

Suggested Solution

In order to address this problem we determined that the offset was a constant value which was location-specific. An offset was allocated to each location in computing the precipitation rate in order to account for this error.

4.4 Recommended Procedures for Integrating Weather in Existing Microscopic Traffic Models and Software (Including Calibration Procedures, Assumptions, and Limitations)

This section describes the state-of-the-art procedures for modeling driver/vehicle car-following, gap acceptance, and lane-changing behavior.

4.4.1 Traffic Simulation Car-Following Models

The modeling of car-following and traffic stream behavior requires a mathematical representation that captures the most important features of the actual behavior. In this treatment, the relationships obtained by observation, experimentation, and reasoning are given: the researcher attempts to express their steady-state behavior in a graphical form and classify them based on their steady-state representation.

Typically, car-following models characterize the behavior of a vehicle (vehicle *n*) that follows a lead vehicle (vehicle *n-1*). This can be presented by either characterizing the relationship between a vehicles' desired speed and the vehicle spacing (speed formulation), or alternatively by describing the relationship between the vehicle's acceleration and speed differential between the lead and following vehicles (acceleration formulation).

Over the last few decades, several car-following models have been developed and incorporated within microsimulation software packages. The analysis conducted describes the characteristics of six of the state-of-practice and state-of-art car-following models, including the Pitt model (CORSIM), Gipps' model

(AIMSUN2), Wiedemann74 and 99 models (VISSIM), Fritzsche's model (PARAMICS), and the Van Aerde model (INTEGRATION).

Based on the analysis of the various longitudinal modeling approaches the following conclusions were made:

1. With regards to the CORSIM software no modifications can be made to the vehicle deceleration behavior to account for weather impacts on driver/ vehicle behavior. Alternatively, the steady-state car-following and acceleration behavior can be modified to capture inclement weather conditions, however this model does not provide sufficient flexibility for use.
2. The Gipps model allows the user to calibrate vehicle deceleration, car-following, and acceleration parameters and thus can reflect inclement weather impacts on driver behavior. The model, however, is incapable of modeling traffic stream stop-and-go waves which might be a problem from a mathematical standpoint but might not be an issue from a practical standpoint.
3. The Fritzsche, Wiedemann99, and Pitt models all use a Pipes steady-state car-following model. The models assume that the speed-at-capacity is equal to the free-flow speed. This approach assumes that the traffic stream average speed is insensitive to the level of congestion on a roadway until the roadway capacity is reached. This assumption is inconsistent with field data from arterial and tunnel data.
4. The Wiedemann74 model assumes that the car-following relationship is convex, which contradicts field observations.

Based on the results of the analysis we recommend the use of either the Van Aerde model, which is incorporated into INTEGRATION or the Gipps model, which is incorporated into AIMSUN2, for steady-state modeling. Summaries of the findings related to car-following models are shown in Table 4.6.

Table 4.6 Microsimulation Car-Following Models

Software	Car-Following Model
CORSIM	• Uses Pitt Model • No modifications can be made to deceleration model • Weather-related factors can be applied to steady-state car-following and acceleration models • Model does not provided sufficient flexibility for use
AIMSUM2	• Uses Gipps Model • Allows the user to calibrate vehicle deceleration, car-following, and acceleration parameters to reflect inclement weather impacts on driver behavior • Incapable of modeling traffic stream stop-and-go waves
PARAMICS	• Uses Fritzche's Model • Average speed is insensitive to congestion until capacity is reached
VISSIM	• Uses Wiedemann74 Models • Assume car-following relationship is convex, contradicting field observations
INTEGRATION	• Uses Van Aerde Model • Concave speed-headway relationship better reflects reality • Incorporates Pipes and Greenshields Models • Incorporates vehicle dynamics Model

4.4.2 Gap Acceptance Models

Within the context of crossing gap acceptance, a gap is defined as the elapsed-time interval between arrivals of successive vehicles in the opposing flow at a specified reference point in the intersection area. The minimum gap that a driver is willing to accept is generally called the critical gap. The Highway Capacity Manual (HCM) defines the critical gap as the "*minimum time interval between the front bumpers of two successive vehicles in the major traffic stream that will allow the entry of one minor-street vehicle*" (Ref 4). When more than one minor street vehicle uses a gap, the time headway between the two minor street vehicles is called the follow-up time. In general, the follow-up time is shorter than the critical gap and equals the inverse of the saturation flow rate.

Gap-acceptance behavior of drivers depends on the driver characteristics and aggressiveness, the roadway geometry, the gap size, the waiting time, and the weather conditions. Mathematical representations of the gap acceptance process are an important component of traffic simulation software. In an attempt to provide a more realistic representation of this behavior, these mathematical descriptions have become more complex by including driver behavior parameters, such as "impatience" or "aggressiveness" associated with various factors. Several methods have been developed to model this behavior, including empirical analysis and theoretical logit and probit models.

Since the critical gap of a driver cannot be measured directly, observations (i.e., accepted and rejected gaps) are used to compute critical gaps, as will be described later. Research efforts since the 1970s have attempted to model driver gap acceptance behavior, including:

- Raff's method;
- Logit models;
- Probit models; and
- Maximum likelihood (ML) models.

Critical gap values can be modeled by either deterministic or probabilistic means. The deterministic critical values are treated as a single average value. The fundamental assumption is that drivers will accept all gaps that are larger than the critical gap and reject all smaller gaps. Although various researchers have used different definitions of critical gap, the deterministic model has been the conventional approach of gap acceptance studies. As an alternative, probabilistic models solve some of the inconsistency elements in gap acceptance behavior by using a statistical treatment of minor street drivers' gap acceptance behavior. This means that drivers' perceptions of a minimum acceptable gap are treated as a random variable (Ref 5).

A logistic linear regression technique for estimating gap acceptance is recommended over the Raff method, which is not suitable for estimating critical gaps**.** Gap estimates developed through the logistic linear regression technique provided a good match with field data, which showed that drivers become more aggressive as they wait longer for a gap and that rain intensity results in an increase in gap size.

4.4.3 Lane-Changing Models

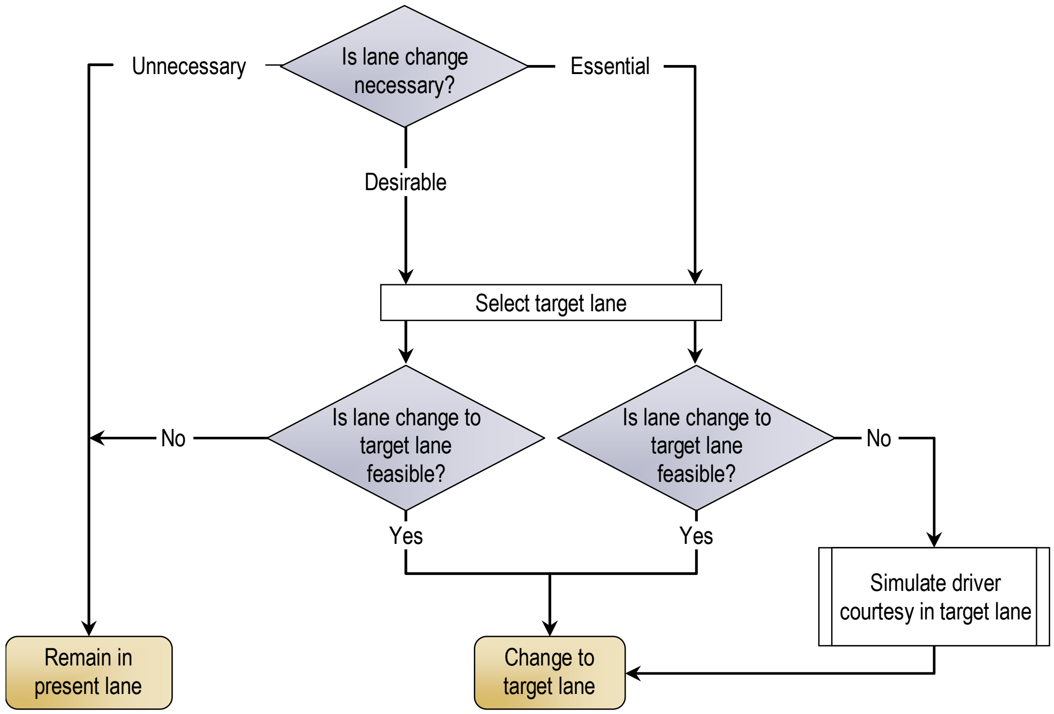
Different types of formulations are used to describe lane-changing models. These models can be categorized as: 1) simulation models; 2) mathematical models; and 3) empirical models. These models are described in this section. Due to limitations in the available data, the lane-changing analysis in this report is not based on field data but on secondary sources of information.

Lane-Changing Simulation Models

A lane-changing model is a microscopic algorithm in which individual vehicle maneuvers are considered in a microsimulation software. The model represents the behavior of the system and the changes over time. A typical simulation model of a traffic facility is usually provided with data, including parameters such as drivers' reaction times and desired speeds.

The overall structure of a lane-changing model is depicted in Figure 4.7. The structure shows only the main components of the process and the relationships among them. Each component is a complex process in itself.

Figure 4.7 The Overall Structure of Hidas' Lane-Changing Model



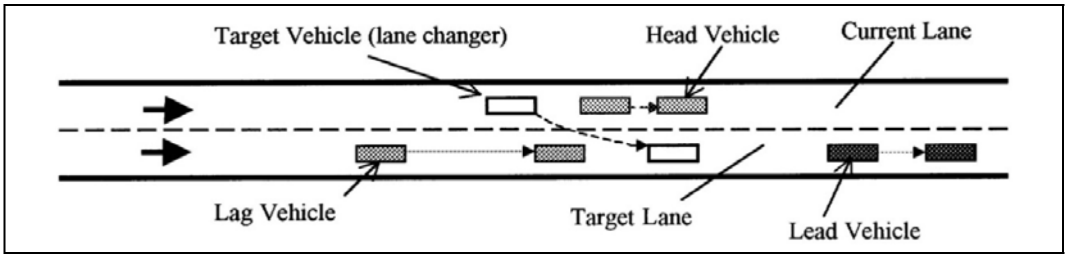
Source: Ref 6.

Lane-Changing Mathematical Models

Lane-changing mathematical models often employ statistical techniques to define the probability of a particular event taking place or to represent a set of traffic characteristics by a theoretical distribution. Because of the complexity of traffic behavior, most mathematical models include a number of simplifying assumptions.

A lengthy observation of lane-changing behavior was conducted on urban streets (Figure 4.8); it analyzed vehicle trajectory data using video-capturing techniques and the VEVID software. On the basis of new findings from observations conducted on four-lane urban streets (two lanes in each direction), a heuristic structure for a lane-changing model was developed. The types of lane changing behavior can be classified into three categories: 1) mandatory; 2) preemptive; and 3) discretionary.

Figure 4.8 Definition of Vehicles Affecting Lane-Changing Behavior

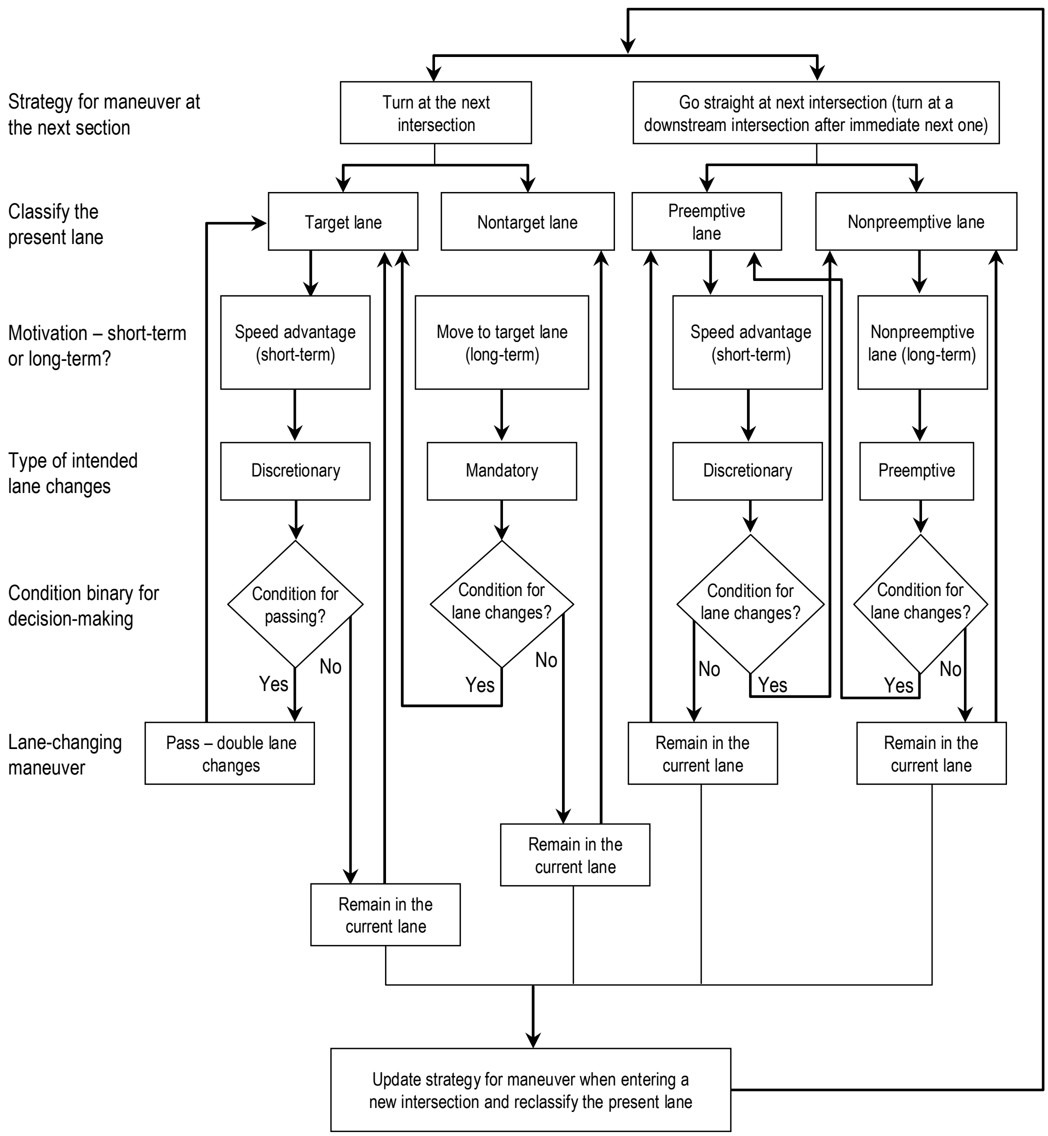


Source: Ref 7.

A mandatory lane change refers to a lane change that a driver has to make before he/she misses a route, is forced to detour, or finds that the current lane is closed ahead. Alternatively, a preemptive lane change refers to a lane change performed to position the driver in the correct lane for an eventual maneuver (e.g., to turn left or right or to get out of the exit lane of the intended closed lane), even though he/she does not intend to make such a maneuver at the next intersection but at some subsequent intersection. Finally, a discretionary lane change refers to a lane change that is executed to pass a slower-moving vehicle. A driver makes a lane change whenever he/she believes the speed of the vehicle ahead in the current lane is intolerable and acceptable gaps are available in the target lane.

From analyses of videotaped observations, rules concerning driver behavior were set up to construct a hierarchy for a lane-changing model, as illustrated in Figure 4.9. The lane-changing process includes three actions: making the decision, recognizing acceptable conditions (gaps or headway between the lead and the lag vehicles), and making the lane-changing maneuver. Three submodels were created. The first model is the decision model which is designed to model the driver's willingness to change lanes and to determine the required type of lane change. The second model is the condition model which involves a search for acceptable conditions to execute a lane change if the driver decides to leave their current lane. The final model is the maneuver model which models the lane-changing maneuver. The primary concerns are duration of the maneuver and how the duration is affected by the vehicle's speed and acceleration just before the maneuver.

Figure 4.9 Lane-Changing Hierarchy



Source: Ref 7.

Lane-Changing Empirical Models

Empirical models typically take the form of an equation in which the variable predicted, the dependent variable, is expressed as a function of a number of independent variables. The equation is usually derived by regression techniques and is based on observed data. Initially the independent variables that improve the fit of the model need to be identified. This process requires a substantial amount of data covering an appropriate range of facilities and independent variables.

As mentioned before, Gipps proposed the concept of speed advantage (SA) to identify the need for a (discretionary) lane change (Ref 8). A quantitative definition of speed disadvantage and SA to describe decisional conditions for a discretionary lane change on urban streets also was proposed by Wei et al. (Ref 7). Tao et al. redefined SA as a perceptual variable with which a driver may compare his or her speed performance with the speed in the adjacent lane(s) and study the speed absorption phenomenon using observed vehicle trajectory data. They also derived the probability that a lane change will be made in response to a speed disturbance via a speed advantage variable and models for acceptable lane-changing decision-making conditions in the adjacent (Ref 9).

Goswami et al. suggested that it is important to compare simulation results to field data (Ref 10). On a multilane freeway it is important to compare the number of lane changes in each lane. It is important to study the frequency of lane changes on multilane freeways to understand and develop capacity models for freeways and improve the geometrics of the multilane freeways to increase safety. Therefore, they studied a one-half-mile section of the I-80 five-lane freeway in California. An on-ramp and a shoulder lane drop is studied and they determined the number of lane changes in terms of origin and destination lanes and their percentages with respect to the entrance volume were presented for each freeway lane to use these analysis data as guidelines for traffic simulation results. Comparison of lane change frequency, towards the shoulder lane and towards the median lane were carried out is presented in (Table 4.7).

Table 4.7 Number of Lane Change from Origin to Destination as Percentage of Entering Volume

		To						
From	**Number of Vehicles Entering**	**1**	**2**	**3**	**4**	**5**	**6**	**Off-Ramp (8)**
1	**870**	**736 (84.6%)**	108 (12.4%)	21 (2.5%)	1 (0.1%)	1 (0.1%)	0	2 (0.2%)
2	**773**	105 (13.7%)	**506 (65.5%)**	117 (15%)	30 (3.9%)	9 (1.1%)	0	6 (0.7%)
3	**591**	28 (4.9%)	164 (27.7%)	**268 (45.3%)**	100 (16.9%)	14 (2.4%)	0	16 (2.7%)
4	**715**	20 (2.8%)	96 (13.4%)	228 (31.8%)	**253 (35.4%)**	67 (9.2%)	0	52 (7.3%)
5	**719**	20 (2.8%)	42 (5.6%)	110 (15.4%)	255 (35.5%)	**219 (30.4%)**	0	74 (10.3%)
6	**751**	2 (0.2%)	5 (0.6%)	28 (3.6%)	99 (13.1%)	394 (52.4%)	0	224 (29.8%)
On-Ramp (7)	**307**	6 (1.9%)	10 (3.2%)	37 (12%)	86 (28%)	155 (50.5%)	0	12 (3.9%)
Total	**4,726**	**917**	**931**	**809**	**824**	**859**	**0**	**386**

Source: Ref 11.

Note: Lane 1 is the median lane and Lane 6 in the shoulder lane. Number of through vehicles in each lane is in bold.

4.5 MODEL VALIDATION REQUIREMENTS AND PROCEDURES

4.5.1 Longitudinal Motion Modeling Procedures

The recommended modeling of longitudinal vehicle motion requires the modeling of steady-state conditions, vehicular deceleration, and vehicular acceleration behavior. As described earlier, there are several approaches to model the steady-state conditions: 1) Pipes model (CORSIM, Paramics, and VISSIM Wiedemann99 model); 2) Van Aerde model; 3) Gipps model; and 4) Wiedemann74 model. The Gipps and Van Aerde models offer the best steady-state modeling approach given that they provide the highest degree of modeling flexibility (speed-at-capacity can be different from free-flow speed). Consequently, these two models are further discussed in terms of steady-state car-following modeling. With regards to vehicle acceleration modeling, both the Gipps and a vehicle dynamics model are recommended. These models also are described.

Steady-State Modeling (Car-Following)

In terms of the Gipps model, it was demonstrated earlier in the report that there is a relationship between microscopic car-following and macroscopic traffic stream parameters.

The model's calibration procedure was applied to a sample dataset gathered along an arterial, as illustrated in Figure 4.10a (Ref 12). The figure demonstrates a reasonable fit to the data, however, given that the data demonstrate that traffic stream speed is sensitive to the traffic stream flow in the uncongested regime; the model offers a suboptimal fit to the field data for the uncongested regime while it presents a good fit for the congested regime. The speed-at-capacity is different from the free-flow speed and thus the model is able to capture this phenomenon.

Alternatively, Figure 4.10b illustrates a sample fit to five-minute data gathered along the Highway 401 in Toronto, Canada. The model fit appears to reflect the field data fairly well except for the congested regime in the speed/flow plane.

The model can be calibrated to reflect inclement weather impacts by adjusting the roadway capacity and speed-at-capacity using weather adjustment factors (WAF). Additionally, the calibration deceleration rate is achieved by modifying the deceleration rate as will be described later in the vehicle deceleration modeling section.

The Van Aerde model was calibrated using the same arterial and freeway data that were presented earlier, as illustrated in Figure 4.11a and 4.11b. The figures demonstrate that the model is extremely flexible and thus capable of providing a good fit to the field data for the entire range of data both in the uncongested and congested regimes. It should be noted that the fit reflects the expected relationship. Differences in driver behavior can be captured by introducing changes to the four traffic stream parameters, namely free-flow speed, speed-at-capacity, capacity, and jam density.

Figure 4.10 Example Illustration of Gipps Model Calibration

(a) Arterial Facility

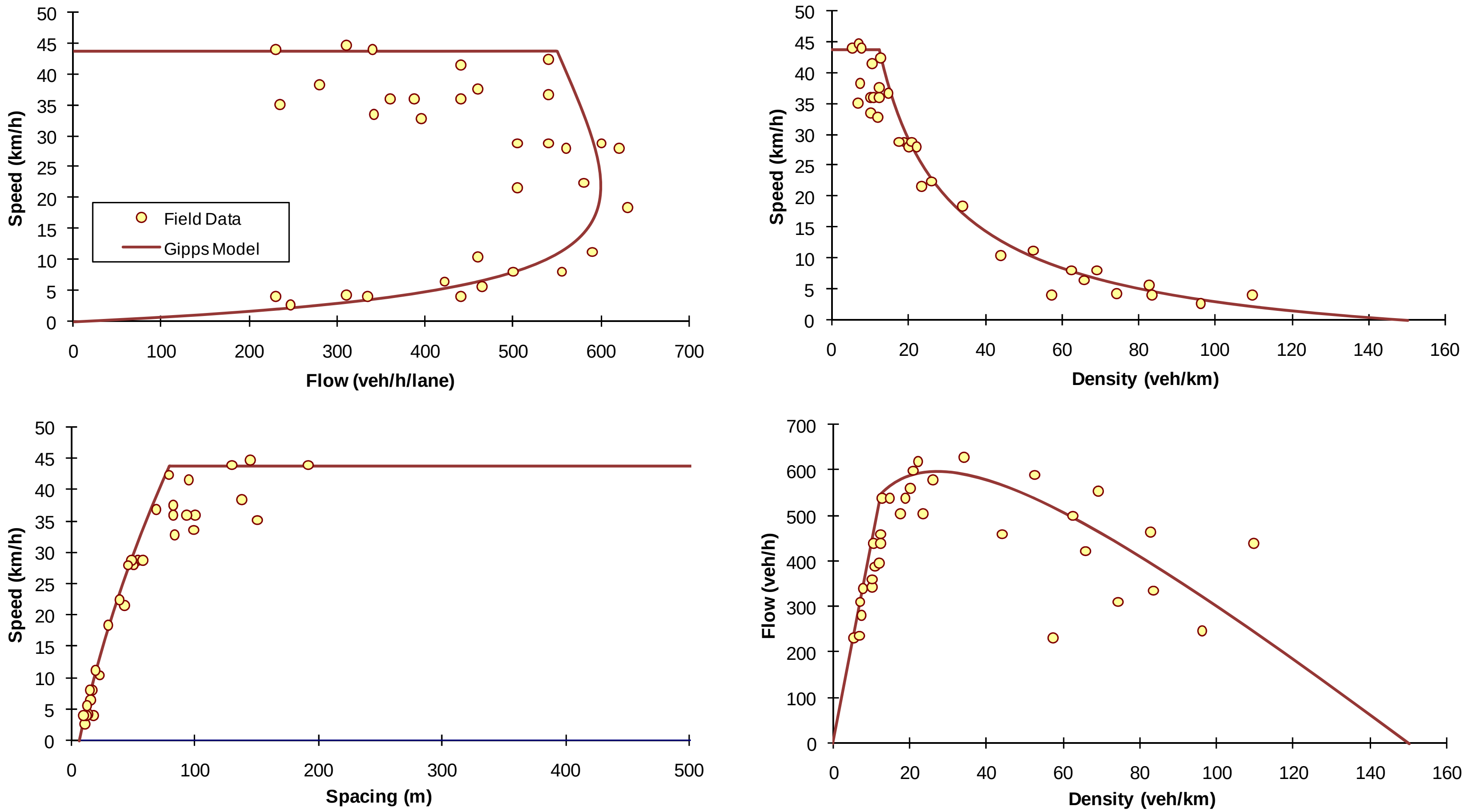


Figure 4.10 Example Illustration of Gipps Model Calibration (continued)

(b) Freeway Facility

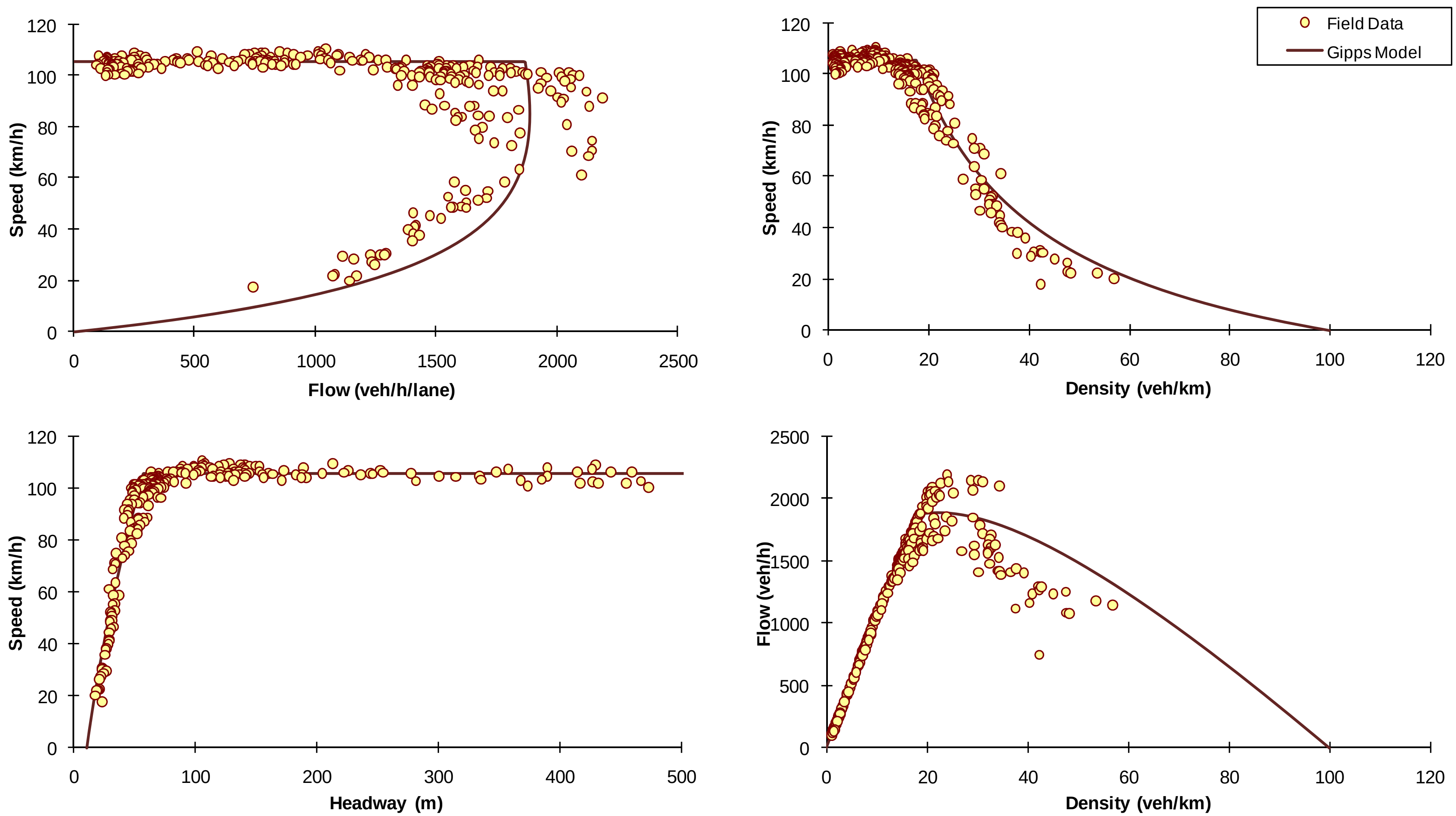


Figure 4.11 Example Illustration of Van Aerde Model Calibration

(a) Arterial Facility

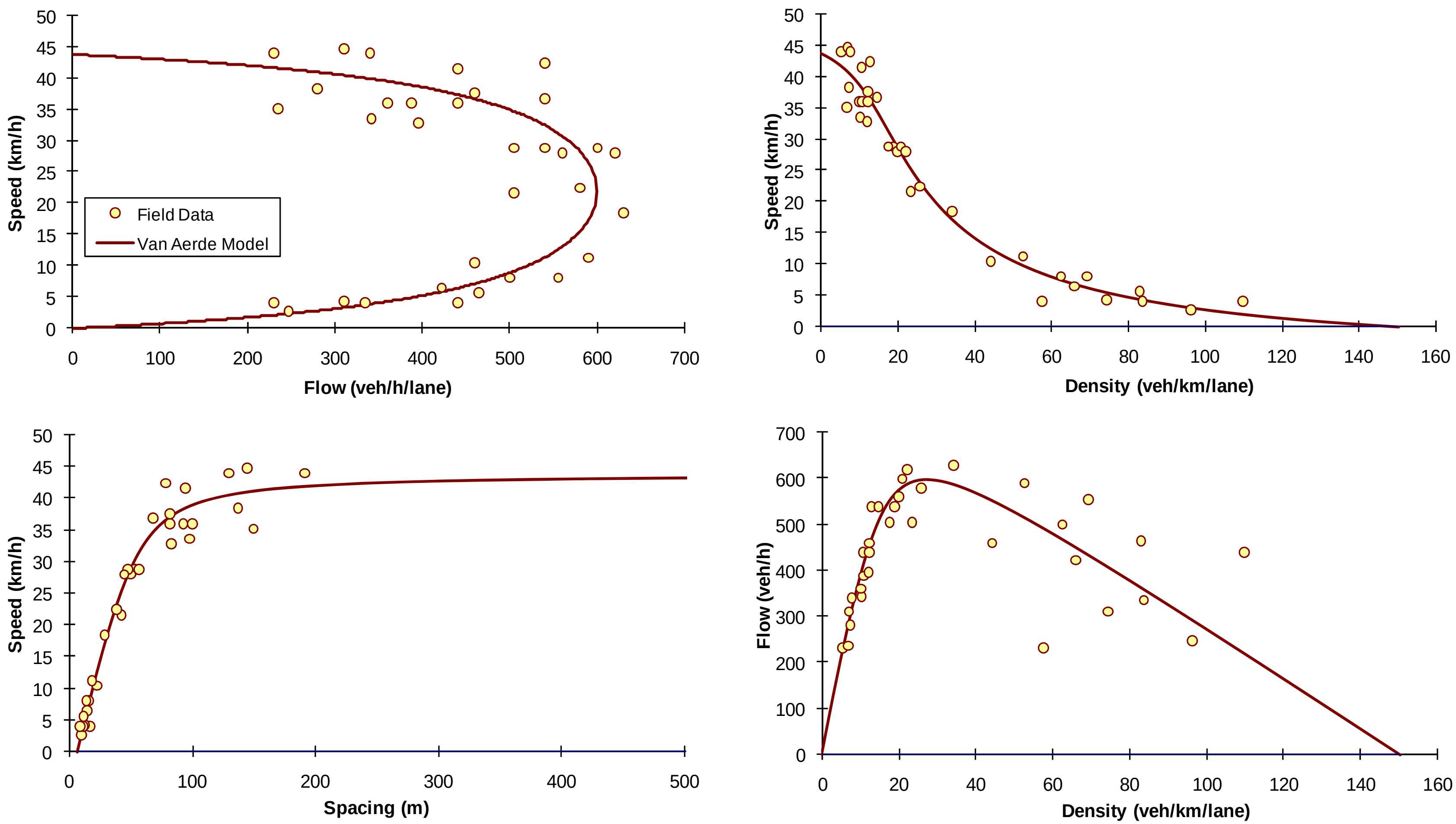
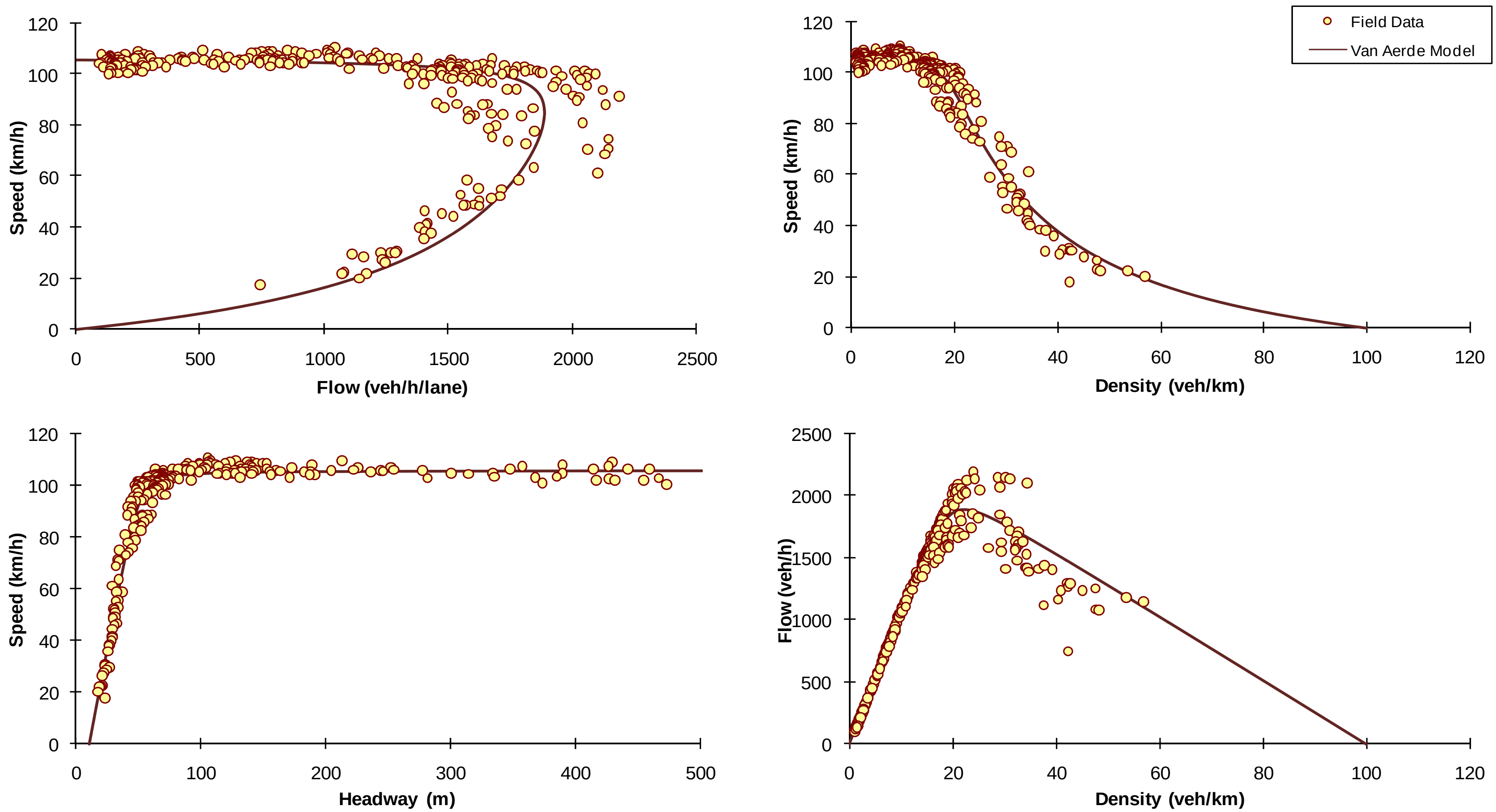


Figure 4.11 Example Illustration of Van Aerde Model Calibration (continued)

(b) Freeway Facility



An earlier FHWA study developed weather adjustment factors (WAF) for three key traffic stream parameters (u_f, u_c, and q_c). These WAFs, which vary as a function of the precipitation type (rain and snow), the intensity level, and the visibility level; can be used to adjust the steady-state car-following models to reflect inclement weather (Ref 13).

Deceleration Modeling

In quantifying the impact of inclement weather on driver deceleration behavior, data from an infrastructure-based radar and video data collection system were utilized. The system measured a variety of state and kinematics parameters (such as brake status, acceleration level, and velocity) for vehicles at five stop-controlled and three four-way signalized intersections for two months at each location. Data were collected and analyzed with the goal of understanding how drivers approach intersections under various approach speeds and environmental conditions.

The typical approach used to model vehicle deceleration is based on the assumption that the vehicle decelerates at a constant rate. This rate cannot exceed the maximum rate that is governed by the roadway surface condition.

The characterization of driver deceleration behavior and the effect of inclement weather on this behavior is conducted using the CICAS-V data.

A regression model was fit to the data, as illustrated in Table 4.8. The response variable considered was the acceleration level in addition to two independent variables: the vehicle initial speed and the rain intensity. The coefficient of determination of the model was 74 percent and both independent variables were found to be significant ($p<0.05$), as summarized in Table 4.8. A test of normality on the response variable demonstrated that there was insufficient evidence to reject the normality hypothesis (Anderson-Darling value of 0.465 and a p-value of 24.6 percent). It should be noted that the slope of the line in the single-variable model (0.03945) is practically identical to that in the two-parameter model (0.0393), and thus the effect of rain intensity is similar regardless of the model.

Using the proposed model the deceleration behavior within microscopic traffic simulation software can be modified to account for the effect of precipitation on driver/vehicle behavior. The maximum deceleration rate is adjusted using a rain adjustment factor that accounts for the impact of rain intensity on the deceleration behavior. Once the maximum deceleration rate is computed, the traffic simulation software can be calibrated.

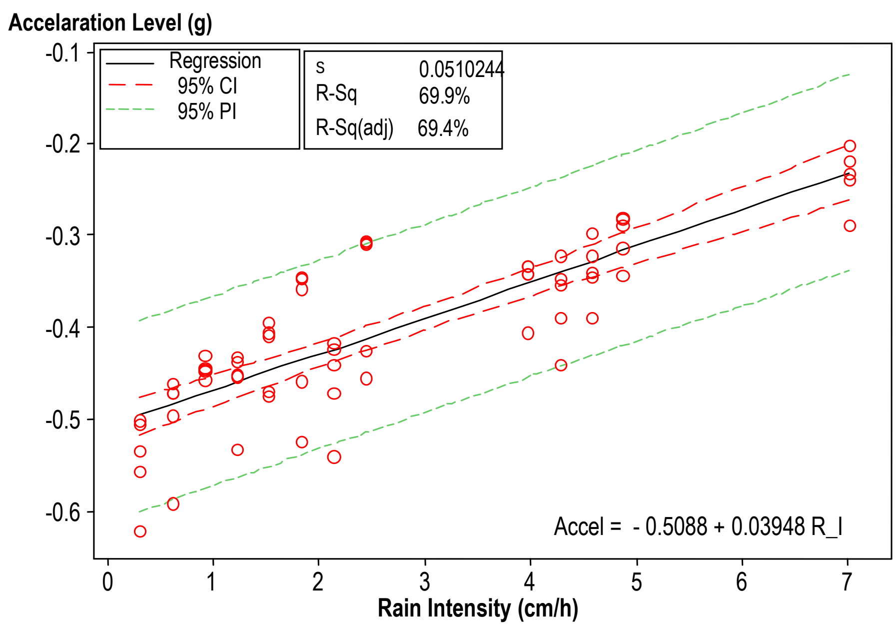
Table 4.8 Impact of Rain Intensity on Driver Deceleration Behavior

Regression Statistics	
Multiple R	0.863
R^2	0.745
Adj. R^2	0.737
Standard Error	0.047
Observations	65

ANOVA

	df	*SS*	*MS*	*F*	*Sig. F*
Regression	2	0.406	0.203	90.558	0.000
Residual	62	0.139	0.002		
Total	64	0.545			

	Coefficients	*Std. Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.4245	0.0272	-15.6240	0.0000	-0.4788	-0.3702
Rain Intensity (cm/h)	0.0393	0.0030	12.9575	0.0000	0.0332	0.0453
Speed (km/h)	-0.0058	0.0017	-3.3477	0.0014	-0.0093	-0.0023



Acceleration Modeling

The modeling of vehicle acceleration can be achieved using a kinematics or a dynamics approach. A kinematics approach, which is used in all simulation software except for the INTEGRATION software, assumes a relationship between vehicle acceleration and speed. This relationship can be assumed to be a linear decaying function of vehicle acceleration as a function of speed or some other form, as will be described in the description of the Gipps model.

Alternatively, the dynamics approach considers all forces acting on the vehicle and computes the acceleration from the resultant force. The latter approach is more appropriate because it explicitly accounts for the roadway surface condition.

This section describes the vehicle dynamics approach first followed by the Gipps vehicle kinematics approach. Subsequently, the models are compared against field data for validation purposes. These models can be calibrated to reflect inclement weather conditions by changing the pavement coefficient of adhesion (friction coefficient) and the rolling coefficient, as will be described in the following subsections.

Vehicle Dynamics Model

Vehicle acceleration is governed by vehicle dynamics. Vehicle dynamics models compute the maximum vehicle acceleration levels from the resultant force acting on a vehicle.

Three resistance forces are considered in the model, namely the aerodynamic, rolling, and grade resistance forces (Ref 10, Ref 14). The aerodynamic resistance varies as a function of the square of the air speed. The rolling resistance is a linear function of the vehicle speed and mass.

The grade resistance accounts for the proportion of the vehicle weight that resists the movement as a function of the roadway grade.

Having computed the various resistance forces, the total resistance force is computed as:

$$R = R_a + R_r + R_g \,. \qquad \text{Eq. 4.1}$$

Gipps Vehicle Kinematics Model

The calibration of the Gipps model entails the identification of two parameters, namely: 1) the maximum desired vehicle acceleration rate (a_{max}) and 2) the driver's desired speed (U_n).

Given that the maximum acceleration occurs as the vehicle speed approaches zero, the maximum sustainable force between the roadway surface and the vehicle tires becomes the governing factor (F_{max}), as illustrated later in Figure 4.12.

The computation of the driver's desired speed (U_n) entails computing the minimum of either a driver-specific free-flow speed or the maximum speed of the vehicle may attain (also known as the equilibrium speed).

Acceleration Model Validation

Because the Gipps model was developed for a single vehicle, no validation has been conducted to evaluate its efficiency considering different vehicle types. The validation of the vehicle dynamics and Gipps acceleration calibration procedure were conducted using data gathered earlier along the Smart Road test facility at Virginia Tech (Ref 15, Ref 16). In addition to documenting all available information on the vehicle and roadway characteristics, the data were gathered under conditions in which vehicle accelerations were not constrained by surrounding traffic. This section summarizes the key parameters associated with the test facility, the test vehicles, and the data collection procedures.

Test Facility

Testing of vehicles was performed on a 1.6-kilometer (one-mile) section of the Smart Road test facility at the Virginia Tech Transportation Institute in Blacksburg, Virginia. The selected test section featured a relatively straight horizontal layout with a minor horizontal curvature that had no effect on vehicle speeds, a good asphalt roadway surface, as well as a substantial upgrade that ranged from 6 percent at one end to 2.8 percent at the other end. Since no flat sections of significant length were available, vehicle accelerations were measured by driving vehicles uphill.

An equation characterizing the grade of the test section was derived from the elevations of 15 stations along the test section. The vertical profile of the test section was then generated by interpolating between station elevations using a cubic spline interpolation procedure at one-meter (3.28-foot) increments. The cubic spline interpolation ensured that the elevations, slopes, and slope rate of change were identical at the boundary conditions (in this case every meter). The grade was then computed for each one-meter section (3.28-foot), and a polynomial regression model was fit to the grade data (R^2 of 0.951) to ensure a smooth transition in the roadway grade while maintaining the same vertical profile.

Test Vehicles

Thirteen light-duty test vehicles in addition to four heavy-duty trucks were used in the study. These vehicles were selected to cover a wide range of light-duty and heavy-duty vehicle combinations, as summarized in Table 4.9. As indicated in the table, the selected vehicles represent a wide range of sizes and a variety of EPA vehicle classes.

Table 4.9 presents the main characteristics of each of the light-duty and heavy-duty vehicles and related parameters for use in the acceleration models described earlier. Below is a description of each of the parameters listed in the table and how the values used in the study were obtained:

- **Vehicle Engine Power –** The engine power can be easily obtained from the vehicle specifications.
- **Engine Efficiency –** Power losses in the engine due to internal friction and other factors generally account for about 20 to 35 percent of the engine losses for light-duty vehicles and about 15 to 25 percent for heavy-duty vehicles. The actual values were computed by minimizing the sum of squared errors

between field-observed power estimates and calibrated power estimates for different efficiency factors.

Table 4.9 Summary of Light Duty Test Vehicle Characteristics

Vehicle	EPA Class	P (kW)	η	Mass (kg)	m_{ta}/m (percent)	A (m^2)	C_d
1996 Geo Metro Hatchback	Subcompact	41.0	0.65	1,130	0.380	1.88	0.34
1995 Acura Integra SE		105.9	0.68	1,670	0.515	1.94	0.32
1995 Saturn SL	Compact	92.5	0.72	1,240	0.560	1.95	0.33
2001 Mazda Protégé LX 2.0		97.0	0.70	1,610	0.525	2.04	0.34
2001 Plymouth Neon		98.5	0.75	1,650	0.495	2.07	0.36
1998 Ford Taurus	Midsize	108.2	0.80	1,970	0.575	2.26	0.30
1998 Honda Accord		111.9	0.75	1,770	0.610	2.12	0.34
1995 BMW 740I		210.4	0.70	2,370	0.515	2.27	0.32
1995 Dodge Intrepid	Large	120.1	0.68	2,040	0.535	2.30	0.31
1999 Ford Crown Victoria		149.2	0.70	2,300	0.590	2.44	0.34
1998 Ford Windstar LX	Minivan	149.2	0.65	2,270	0.550	2.73	0.40
1995 Chevy S-10	Pickup	145.47	0.72	1,930	0.605	2.31	0.45
1995 Chevy Blazer	SUV	145.47	0.65	2,310	0.560	2.49	0.45
Cummins Engine	Heavy-duty	260	0.88	Variable	~0.37	10.7	0.78
Detroit Diesel	Heavy-duty	320	0.88	Variable	~0.37	10.7	0.58
Detroit Diesel	Heavy-duty	350	0.88	Variable	~0.37	10.7	0.58
Detroit Diesel	Heavy-duty	375	0.88	Variable	~0.37	10.7	0.58

- **Vehicle Mass –** Vehicle mass is an important parameter in the model as it determines the force required to accelerate a vehicle. Vehicle weights were obtained using General Electrodynamics Corporation (GEC) weigh scales with an advertised accuracy of 98 percent.
- **Percentage of Vehicle Mass on the Tractive Axle –** Each axle was weighed separately. In the case of light-duty vehicles, typical values for front-wheel drive vehicles are in the range of 50 to 65 percent, reflective of the high weight of the engine sitting on top of the axle. For rear-wheel drive vehicles, the mass on the tractive axle typically ranges between 35 to 50 percent of the total mass.
- **Frontal Area –** The frontal area of the vehicle can be approximated as 85 percent of the height times the width of the vehicle (if it was not given directly in the vehicle specifications).

- **Air Drag Coefficient –** The air drag coefficient is given in the vehicle specifications. Typical values for light-duty vehicles range from 0.30 to 0.35, depending on the aerodynamic features of the vehicle. Heavy-duty vehicles have much higher drag coefficients ranging from 0.58 to 0.78.

Each of the heavy-duty trucks was tested for at least 10 weight configurations along the Smart Road test facility. Moreover, two of the trucks were tested without a trailer in order to cover the fairly low weight-to-power ratios that were observed in the field. The test scenarios covered a range of weight-to-power ratios from 24 kg/kW to 171 kg/kW (39 lb/hp to 282 lb/hp), covering a wider range than what is observed in the field. The truck powers ranged from a minimum of 260 kW (350 hp) to a maximum of 375 kW (500 hp), covering a substantial range of field truck characteristics (85 percent of the field observations). It also should be noted that the trucks included engines that were developed by different engine manufacturers for different model years. All trucks were manual and were equipped with radial tires, which is consistent with a field survey conducted earlier.

Data Collection Procedures

Each of the test vehicles was subjected to the same set of tests. The test runs involved accelerating the vehicles from a complete stop at the maximum acceleration rate over the entire length of the 1.6-kilometer test section from 0 km/h to the maximum attainable speed within the test section. Depending on the type of vehicle, maximum speed attained by the end of the test section for light-duty vehicles varied between 128 and 160 km/h (80 and 100 mph) and was much lower for the heavy-duty trucks. In conducting the study, a minimum of five repetitions were executed for each test set in order to provide a sufficient sample size for the validation analysis.

In each test run, the speed and the position of the vehicle were recorded using a portable Global Positioning System (GPS) receiver connected to a laptop. Outputs from the GPS receiver included latitude, longitude, altitude, speed, heading, and time stamp once every second. Nominal position accuracy was specified with a 25-meter (82-foot) spherical error probability, while nominal velocity accuracy was specified within 0.1 meters per second (0.31 feet per second) error probability.

Roadway Parameters

To apply the vehicle dynamics model, parameters linked to roadway characteristics must be determined: pavement type, pavement coefficient of friction, roadway grade, rolling coefficients, and altitude of roadway.

- **Pavement –** The pavement type and condition are required to determine several parameters. As indicated earlier, the selected test section on the Smart Road facility had a Pavement Serviceability Index greater than 3.0 and thus was classified as “good.” The pavement condition affects the coefficient of friction and rolling coefficients (Ref 14). Consequently, a coefficient of friction of 0.6 and values of 1.25, 0.0328 and 4.575 were selected for the coefficients C_r, c_2 and c_1, respectively.

- **Grade –** The roadway grade was computed at each vehicle position.
- **Altitude –** This is the altitude above sea level for the testing location, in meters. Since the Smart Road sits at an altitude of 600m, this lead to determination of an altitude coefficient of 0.95 (Ref 14).

Model Calibration Validation and Comparison

For illustration purposes, the results obtained for three of the light-duty vehicles and one of the heavy-duty trucks considering two loads are presented in this section. The three light-duty vehicles include a subcompact low-powered vehicle (Geo Metro), a very powerful midsized vehicle (BMW 740I), and a light-duty truck (Chevy Blazer). These vehicles were selected to represent the full range of possible light-duty vehicle configurations. Additionally, two extremes of heavy-duty vehicle loadings were considered (empty versus fully loaded).

The input parameters for the vehicle dynamics model together with the calibrated Gipps model parameters are summarized in Table 4.10. The last two parameters are highlighted in grey because they represent parameters for a flat surface (grade of 0 percent).

Table 4.10 Model Input Parameters for Calibration Purposes

		Vehicle				
	Parameter	Geo Metro	BMW 740I	Chevy Blazer	Truck (Trailer)	Truck (Full Load)
Vehicle Dynamics Model	w (kg/kW)	28	11	16	87	172
	P (kW)	41	210	145	260	260
	m_{ta} (percent)	0.45	0.49	0.50	0.36	0.37
	H (m)	599	599	599	599	599
	η_d	0.65	0.70	0.65	0.88	0.88
	μ	0.60	0.60	0.60	0.60	0.60
	C_d	0.34	0.32	0.45	0.78	0.78
	C_h	0.95	0.95	0.95	0.95	0.95
	C_1	0.04729	0.04729	0.04729	0.047285	0.047285
	C_2	0.0328	0.0328	0.0328	0.084	0.084
	C_3	4.575	4.575	4.575	4.575	4.575
	C_r	1.75	1.75	1.75	0.125	0.125
	A (m^2)	1.88	2.27	2.49	10.7	10.7
Gipps Model	Ka	2.539E-05	1.375E-05	2.177E-05	1.653E-05	8.359E-06
	K_{r1}	5.629E-04	5.629E-04	5.629E-04	1.030E-04	1.030E-04
	K_{r2}	7.851E-02	7.851E-02	7.851E-02	5.608E-03	5.608E-03
	K_T	7.843E+01	1.917E+02	1.360E+02	2.489E+01	1.259E+01
	a^0_{max} (m/s^2)	2.57	2.80	2.86	0.89	0.74
	U_n (km/h)	131.17	218.78	168.94	127.11	120.52

The proposed calibration procedure produces a good match to the field data in the case of light-duty vehicles, as illustrated in Figure 4.12. These results are consistent for the subcompact, midsize, and light-duty truck vehicles. Moreover, the results demonstrate that the Gipps model appears to be sufficient for the modeling of vehicle acceleration behavior. The only shortcoming that can be identified is that the shape of the speed-acceleration relationship is concave in the case of the Gipps model, while in reality it is convex at higher vehicle speeds.

In the case of the modeling of heavy-duty truck acceleration behavior, the Gipps model appears to be adequate for light truck loads, as illustrated in Figure 4.13a. However, the Gipps model does not provide a good match to the field data for the modeling of heavy truck acceleration behavior, as clearly illustrated in Figure 4.13b.

Figure 4.12 Sample Model Calibration (Light-Duty Vehicles)

(a) 1996 Geo Metro

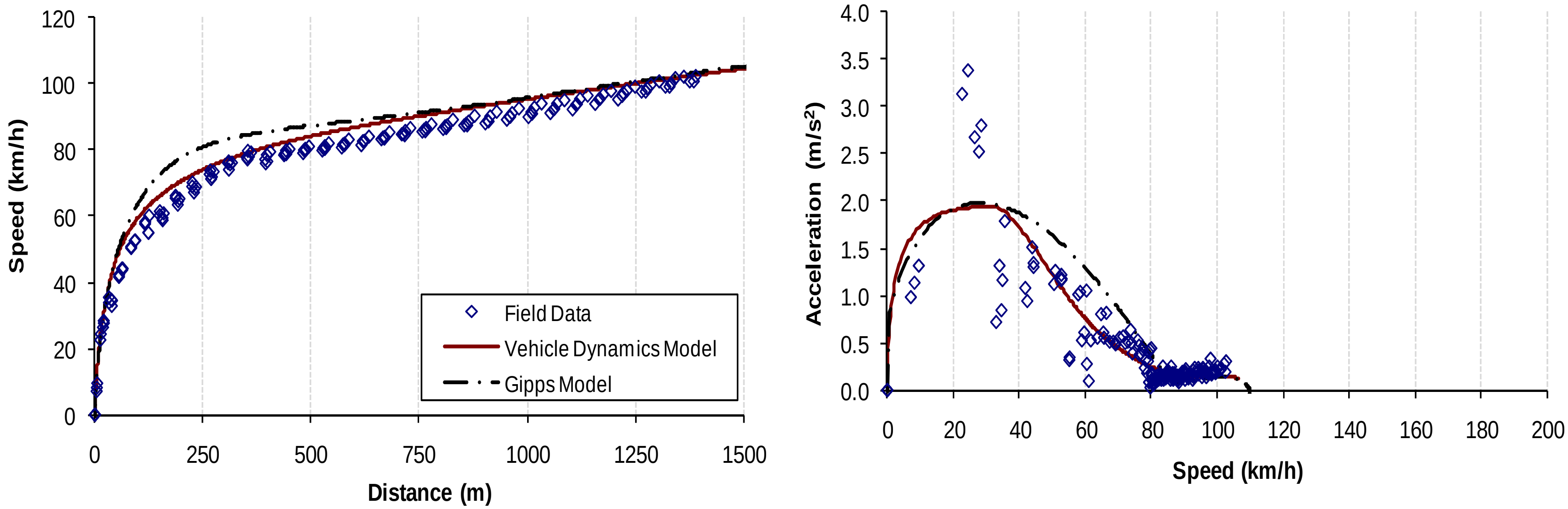


Figure 4.12 Sample Model Calibration (Light-Duty Vehicles) (continued)

(b) 1995 BMW 740I

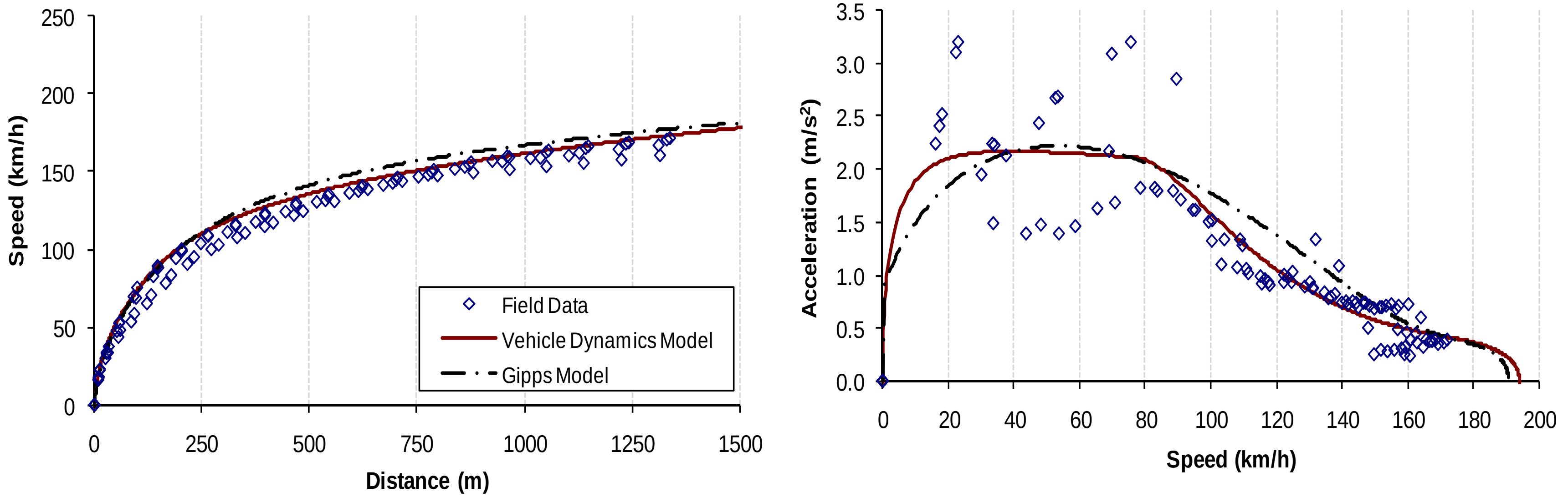


Figure 4.12 Sample Model Calibration (Light-Duty Vehicles) (continued)

(c) 1995 Chevy Blazer

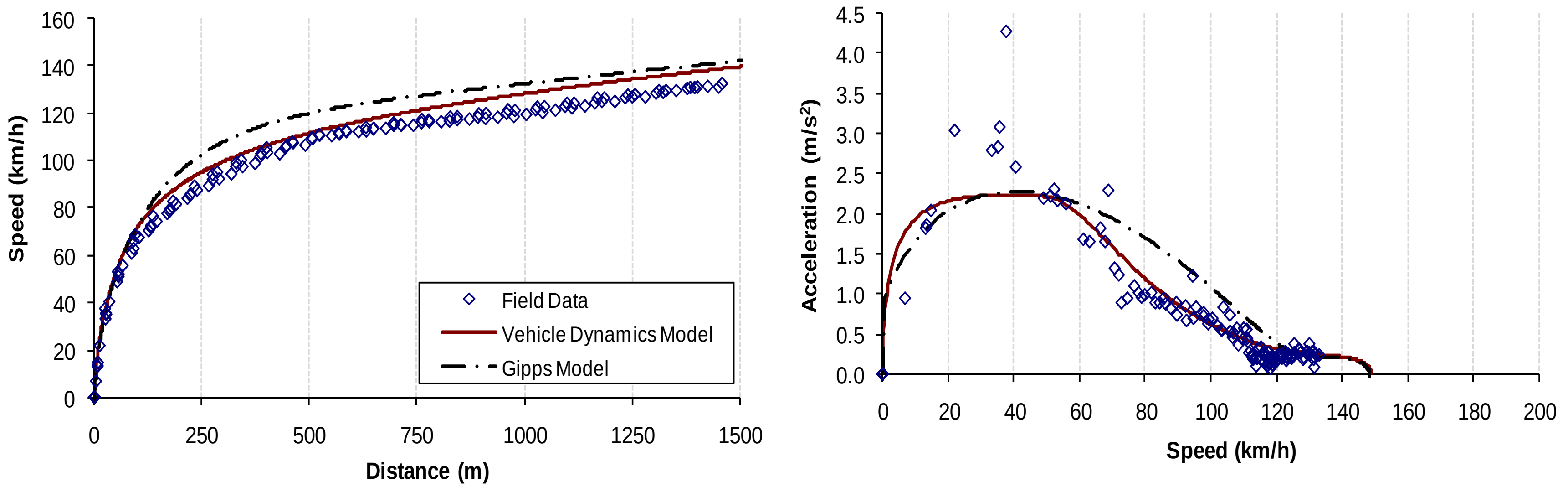


Figure 4.13 Sample Model Calibration (Heavy-Duty Vehicles)

(a) Empty Truck (Weight-to-Power Ratio = 87 kg/kW)

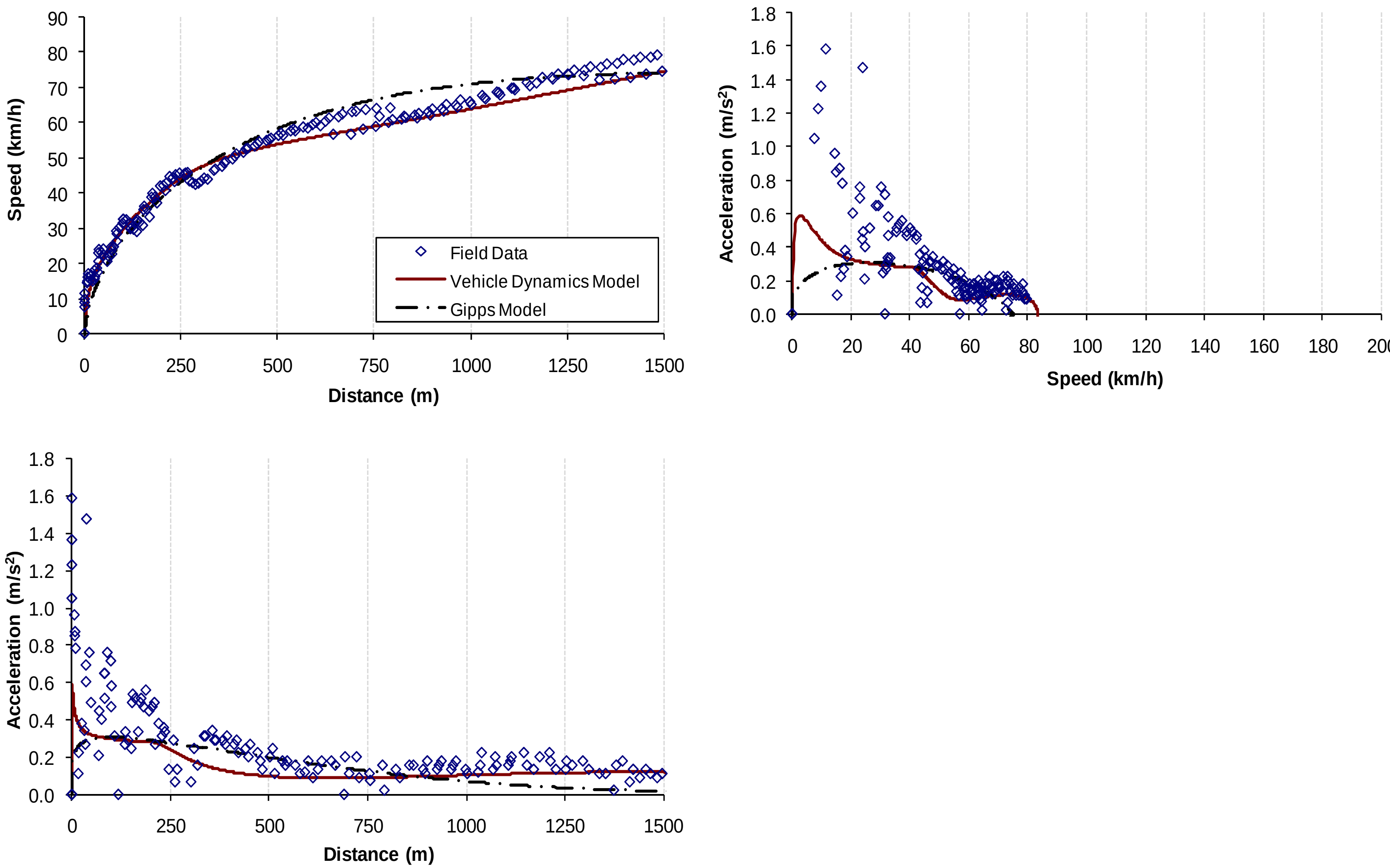
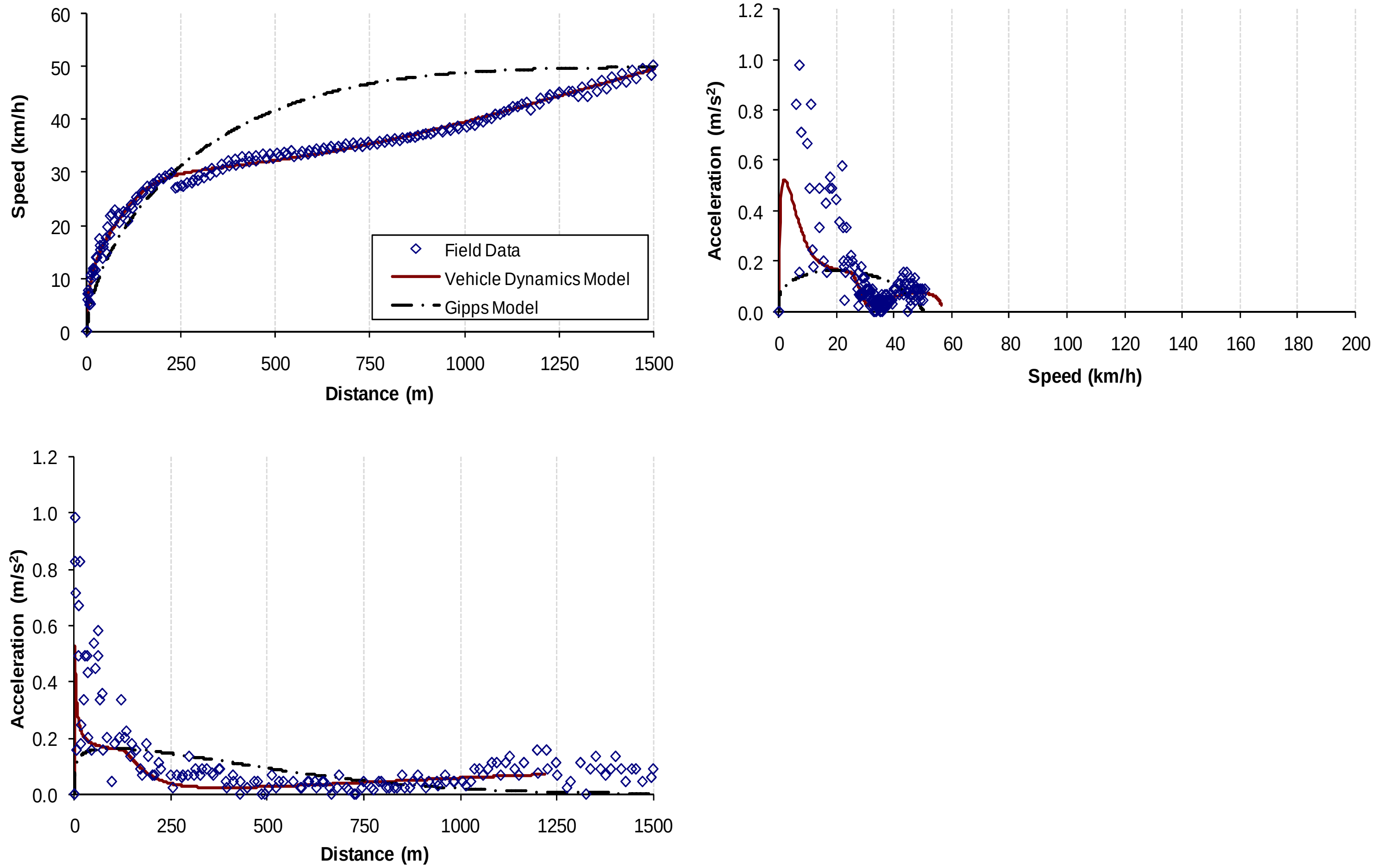


Figure 4.13 Sample Model Calibration (Heavy-Duty Vehicles) (continued)

(b) Fully Loaded Truck (Weight-to-Power Ratio = 172 kg/kW)



Because the CICAS-V data do not include data within the intersection, the acceleration data may be limited. The team currently is analyzing the acceleration data to investigate the possibility to develop relationships similar to those developed for deceleration behavior. In the event this was found impossible, then the acceleration behavior will be modified by adjusting the roadway adhesion and rolling coefficients to account for changes in the road surface conditions.

4.5.2 Gap Acceptance Modeling

Gap acceptance models are used to model the decision to execute a lane change or to accept a gap while moving through an opposing flow. This procedure entails developing models that capture the driver's gap acceptance behavior. We are proposing the use of either a probit or logit model structure.

Proposed gap acceptance models that will be considered in the analysis include a nondimensional model of the form

$$\mathrm{Logit}[p] = \beta_0 + \beta_1 \frac{h}{\overline{\tau}} + \beta_2 \frac{w}{g} + \beta_3 \frac{r}{\overline{r}}, \tag{4.2}$$

and a dimensional model of the form

$$\mathrm{Logit}[p] = \beta_0 + \beta_1 \left(h - \overline{\tau}\right) + \beta_2 w + \beta_3 r\,. \tag{4.3}$$

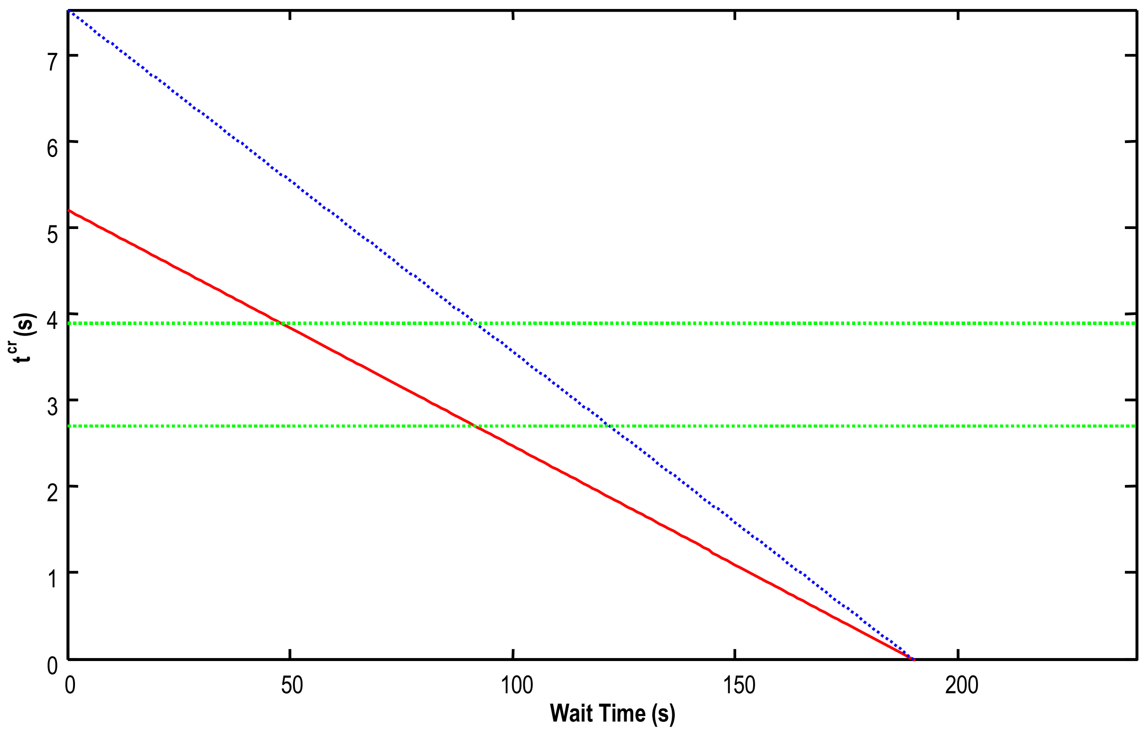
Here p is the probability of accepting a gap; h is the headway between successive vehicles in the opposing flow (s); τ is the average time required by the subject vehicle to clear a conflict point (s); w is the time the driver waits in search for a gap (s); g is the duration of the green time (s); r is the rain intensity (cm/h); and variables with a bar on top are average estimates.

The critical gap is computed as the gap for which the probability of acceptance is 0.5. The calibration of the critical gap requires analysis of the CICAS-V data to develop rain adjustment factors. Unfortunately, the CICAS-V data does not include any snow effects on driver gap acceptance behavior.

In the case of the above mentioned models the critical headway is computed as $h_c = \overline{\tau} - \frac{\beta_0}{\beta_1} - \frac{\beta_2}{\beta_1} w - \frac{\beta_3}{\beta_1} r$ and $h_c = -\frac{\beta_0}{\beta_1}\overline{\tau} - \frac{\beta_2}{\beta_1}\overline{\tau}\frac{w}{g} - \frac{\beta_3}{\beta_2}\overline{\tau}\frac{r}{\overline{r}}$. (4.4)

The models demonstrate that drivers become more aggressive as they wait longer in search of a gap, as illustrated in Figure 4.14.

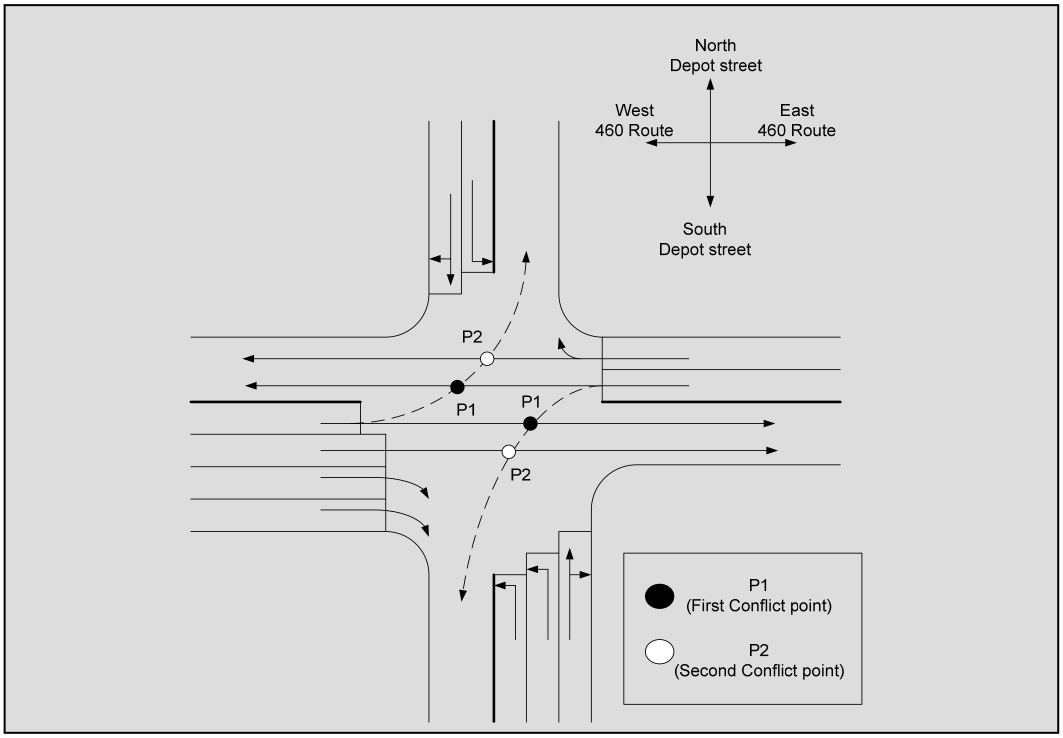
Figure 4.14 Variation in Critical Gap as a Function of Driver Wait Time



This section summarizes the results of a gap acceptance analysis conducted by VTTI for this project. The main objectives of this study were to investigate the influence of the waiting time and rain intensity on left-turn gap acceptance behavior, critical gap value, and traffic capacity under three hypotheses, as follows: 1) drivers become more aggressive as they wait longer in search of an acceptable gap; 2) driver' require longer gaps under rainy conditions; and 3) the size of a driver's acceptable gap increases as crossing more than one opposing lane.

The data used for this study is obtained from the CICAS-V study. The study site is the signalized intersection of Depot Street and North Franklin Street (Business Route 460) in Christiansburg City, Virginia. A schematic of the intersection is shown in Figure 4.15. It consists of four-leg approaches at approximately 90-degree angles. The posted speed limit for the eastbound and northbound is 35 mph and for the westbound and southbound is 25 mph.

Figure 4.15 The Signalized Intersection of Depot Street and North Franklin Street (Business Route 460) in Christiansburg City, Virginia



In the dataset, 2,730 gap decisions from a total of 300 left-turning movements were recorded after excluding accepted gaps terminated by red signal (no following vehicle). The 2,730 observations were divided into 2,017 observations in the dry condition and 713 observations in rain condition.

As indicated before, the primary objective of this study was to quantify the dependence of gap acceptance decisions on wait time, rain intensity and travel time. The logistic regression analysis is utilized in this study to fit the data as a statistical technique for developing predictive models for the probability (P) that an event (such as the acceptance of a gap) will or will not occur, as shown in Equation (4.5):

$$P = \frac{e^{U(x)}}{1+e^{U(x)}} \tag{4.5}$$

$$U(x) = Logit[P] = \ln\left[\frac{P}{1-P}\right] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \tag{4.6}$$

Where; P is the probability of accepting a gap; $x_1, x_2, \ldots, x_n$ are the independent variables affecting the probability of gap acceptance; and $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ are the estimated regression coefficients. In this study, three different models are considered to present the gap acceptance behavior in terms of different variables (gap size, waiting time, accepted gap lane number, and rain intensity).

The results of the analysis showed that each of the three models has similar inferences concerning the relation between gap acceptance, waiting time, rain intensity, and lane number (or travel time). Each of these models predicts that for a given gap duration and waiting time, the probability that a driver accepts that gap decreases as the rain intensity increases and that at a given gap size and rain intensity the probability of accepting this gap increases as the waiting time increases for a specific opposing lane. To illustrate this effect, Figure 4.16 displays the probability of gap acceptance versus gap size for each of the three models, in which the waiting time and rain intensity are fixed values equal to 0 in order to plot a two-dimensional plot. Otherwise the plot would be four-dimensional.

Generally, the larger the available gaps, the higher the probability that drivers will accept the gaps. The critical gap is defined as the gap size that has the same number of accepted and rejected observations; therefore, it is corresponding to the median of the probability of accepted gaps, which is accepted by 50 percent of the drivers, as shown in Figure 4.16.

To explore the relationship between the critical gap and the wait time or rain intensity, the critical gap is plotted versus the wait time and rain intensity at constant rain intensity and wait time, respectively. In general, the relationship between the waiting time and critical gap size "t_c" is a linear decay function, i.e., when the driver is waiting longer, the driver will become more aggressive and the critical gap value decreases, while increasing the rain intensity, drivers are willing to accept bigger gaps. The effect of the rain intensity and waiting time on the critical gap value for each lane (first lane and second lane) is shown in Figure 4.16. It is assumed in plotting the relation between waiting time and the critical gap, or the rain intensity and the critical gap that the other independent variable is held constant, to show the effect of each of these independent variables on the critical gap value for the first and the second lane.

For M1, in Figure 4.16, the slope of the line for the second lane is much steeper than the first lane; which cause the intersection of these two lines at waiting time approximately equal 70 seconds, that means that after waiting 70 seconds, the driver is willing to accept a shorter gap in the second lane than the first lane, which is unrealistic. Figure 4.16 shows that the difference between the critical gap size for the first and the second lane is 0.9 seconds at rain intensity 0 cm/hr and the difference increases with rain intensity. The difference becomes 3.5 seconds at rain intensity of 10 cm/hr.

For M2, Figure 4.16, it is noticeable that by increasing the waiting time or the rain intensity, the difference between the critical gap value for the first and second lane remains constant and equal to 1.2 seconds which is equal to the difference in travel-time value between the first and second conflict points (P_1 and P_2).

For M3, the difference in the critical gap for the first and second lane remains close to constant at around 2.5 seconds which is double the difference in travel-time values between the first and second conflict points. This difference is clearly unrealistically large.

From field observations and data analysis, this analysis showed in general that an increase in waiting time to accept a gap causes drivers to become more aggressive and willing to accept smaller gaps. Therefore the critical gap value and follow up time decrease. On the other hand, increasing rain intensity may contribute to significant increases of the critical gap, as well as follow-up time, because drivers need more response time to decide to accept the available gap.

4.5.3 Lane-Changing Models

Different types of models are used to describe lane-changing behavior. These models can be categorized as: 1) simulation models; 2) mathematical models; and 3) empirical models. These models are briefly described.

Lane-Changing Simulation Models

A lane-changing model is a microscopic algorithm in which individual vehicle maneuvers are considered in microsimulation software. The model represents the behavior of the system and the changes over time. A typical simulation model of a traffic facility is usually provided with data, including parameters such as drivers' reaction times and desired speeds.

Lane-Changing Mathematical Models

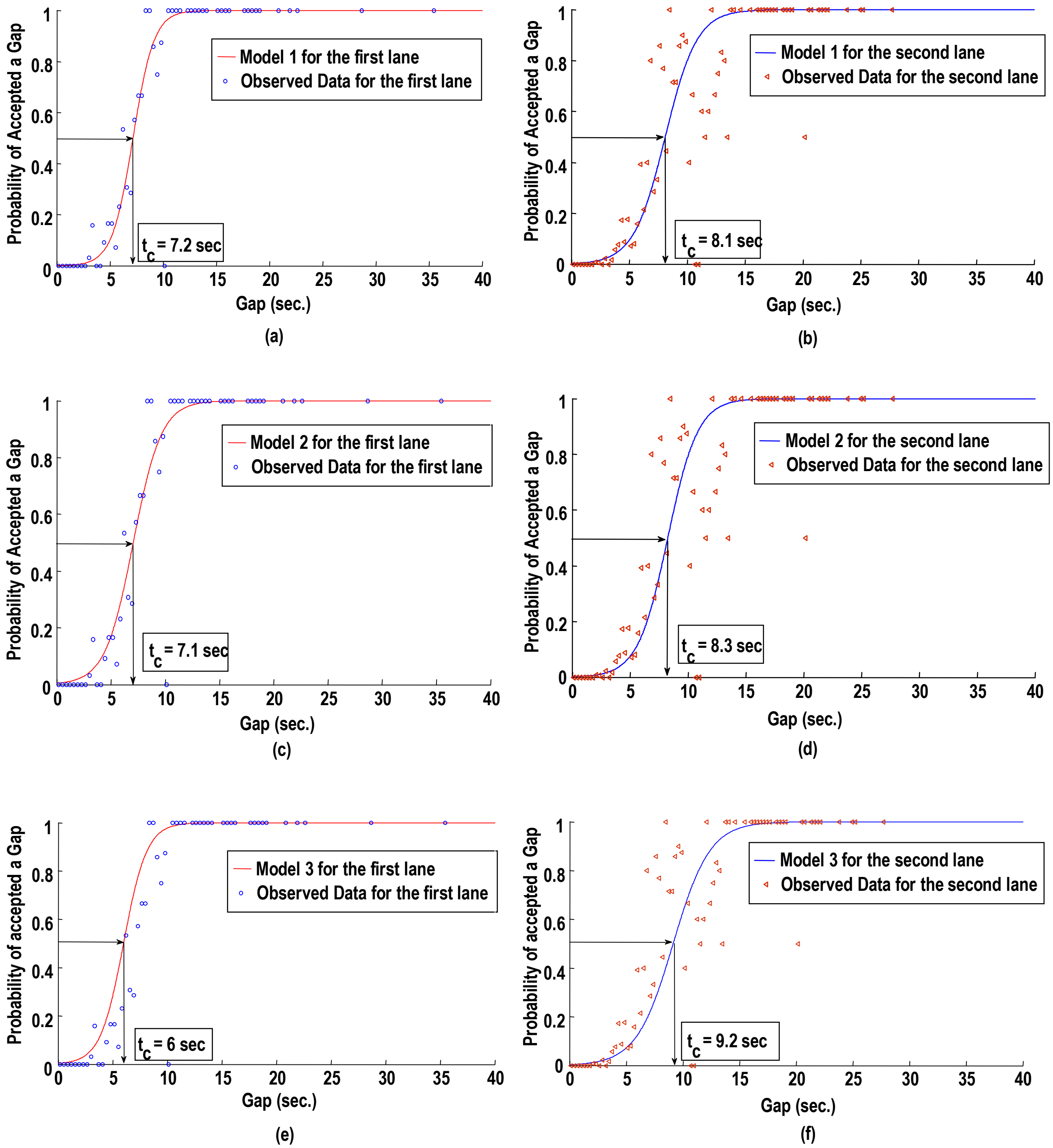
Lane-changing mathematical models often employ statistical techniques to define the probability of a particular event taking place or to represent a set of traffic characteristics by a theoretical distribution. Because of the complexity of traffic behavior, most mathematical models include a number of simplifying assumptions.

Lane-Changing Empirical Models

Empirical models typically take the form of an equation in which the variable predicted, the dependant variable, is expressed as a function of a number of independent variables. The equation is usually derived by regression techniques and is based on observed data. Initially the independent variables that improve the fit of the model need to be identified. This process requires a substantial amount of data covering an appropriate range of facilities and independent variables.

Given that the project was not able to gather any data on lane-changing behavior it is not possible to capture the impact on inclement weather on lane-changing behavior at this point. It is the conclusion of the research staff that lane-changing behavior can be incorporated into all of the reviewed simulation packages by adjusting the gap acceptance parameters. A discussion of how lane-changing parameters could be incorporated into specific microsimulation packages is included in Section 5.0.

Figure 4.16 The Probability Distribution and the Critical Gap Values for the Different Proposed Models
For the First and Second Opposing Lane



4.6 SOFTWARE AND OTHER COMPUTATIONAL REQUIREMENTS

Computational requirements for the simulations described in this report are minimum and do not pose any additional computation on existing software. Modern-day laptop and desktop computers can handle the analysis presented here. Two different sets of tools were used to conduct the analysis.

Both the 100-Car and CICAS V datasets were compiled using the Data Analysis and Reduction Tool (DART). DART is a custom-built software that was developed at VTTI for synchronizing video and kinematics data. The DART software is integrated with SQL Server 2005 and all data are stored in SQL databases that have the same data structure regardless of the study application. Within DART, users can code different filters and robots to extract subsets of the dataset. To facilitate the data analysis, custom Matlab codes will be developed to extract vehicle trajectory data to conduct the analysis.

In the CICAS-V data collection effort, data were collected and analyzed with the goal of understanding how drivers approach intersections under various approach speeds and environmental conditions. The data acquisition system (DAS) employed a suite of hardware and software to record information about vehicles that approached the test sites. The DASs consisted of three major subsystems: 1) sensing network; 2) processing stack; and 3) associated hardware enclosures and mounts.

4.7 CONCLUSIONS OF ANALYSIS

The research presented in this section describes the two data sources that could be used to conduct the analysis of car-following, lane-changing, and gap acceptance behavior. The various data fields and the potential challenges relating to the data were identified. The study concludes that because the 100-car data set has problems with the data timestamps, a direct link between traffic and weather data cannot be established. Furthermore, current naturalistic data do not provide the lane in which a target vehicle is located and thus the data could not be used for lane-changing or gap acceptance analysis. Alternatively, the CICAS-V data does include weather stations at the signalized intersections and does track all vehicles approaching the signalized intersection. Unfortunately the data are only available for a limited length (100 meters upstream of the intersection) so they can only be used for characterizing driver deceleration, and potentially acceleration behavior. In addition, the CICAS-V data includes video data that can be used for the analysis of driver gap acceptance behavior. The CICAS-V data, however, were only gathered in the summer months so the effect of snow precipitation of driver behavior could not be analyzed without additional data gathering that was not part of the project.

With regards to car-following behavior the study presented different approaches to modeling car-following behavior. These approaches were compared and the study demonstrated that the Van Aerde and Gipps models provide the highest level of flexibility in capturing driver behavior under multiple regimes across different roadway facility types. Procedures for calibrating the steady-state behavior of various car-following models also were developed using macroscopic loop detector data. In order to account for inclement weather effects, adjustment to the steady-state parameters can be achieved using weather adjustment factors developed in the earlier FHWA study.

The modeling of vehicle deceleration behavior is achieved by introducing a maximum deceleration level. In modeling inclement weather conditions, the maximum deceleration level can be modified to account for the reduction in the roadway adhesion conditions. These modifications were developed using the CICAS-V data for all vehicles arriving at the Pepper's Ferry Road/SR 460 intersection. Alternatively, the modeling of vehicle acceleration behavior is achieved through the use of either vehicle kinematics or vehicle dynamics models. The use of a vehicle dynamics model is more appropriate because roadway surface parameters can be directly adjusted within the model.

Lane-changing behavior is usually modeled in three steps: 1) the decision to consider a lane change; 2) the decision to execute a lane change; and 3) the actual execution of the lane change. Item 1 is something that cannot be measured in the field, while Item 2 is modeled using gap-acceptance procedures similar to what was presented on the gap acceptance analysis. The actual execution of lane changing can be captured using the car-following procedures that were described earlier. Because no data were available to conduct this analysis the modeling of lane-changing behavior was not implemented.

Gap acceptance behavior is used to model a driver's decision to accept a gap through an opposing flow, in the case of a permissive left turning vehicles at a signalized intersection or vehicles at a two-way stop sign crossing the main street. In addition, gap acceptance procedures are used for the modeling of a driver's decision to make a lane change. The modeling of gap acceptance behavior is achieved through the use of either logit or probit models. Adjustment factors can be included in these models to account for the effect of inclement weather on a driver's gap acceptance behavior.

The CICAS-V data were used to conduct the gap analysis for this project. Gap acceptances were calculated from video taken at the three intersections. Three models were hypothesized and the coefficients in all of the models were determined by fitting the extracted data using a generalized linear regression model. A "boot-strapping" technique was used. Eighty percent of the data, randomly selected, was used to estimate the model while the other 20 percent was used for validation. The process was repeated multiple times (5,000) until the mean and standard deviations of these coefficients remained relatively constant. The project team was able to identify a model that could be used to adjust gap acceptance for rainy conditions but no snow conditions were experienced during the data collection period.

5.0 Procedure Implementation in Traffic Simulation Software

5.1 Structure for Microsimulation Weather Adjustment Factors

The overall framework of this effort was developed as part of an earlier project and documented in that publication (Ref 13). The work involved development of weather adjustment factors (WAF) for three key traffic stream parameters (u_f, u_c, and q_c). These WAFs vary as a function of the precipitation type (rain and snow), intensity level, and visibility level as:

$$WAF = a_1 + a_2\ i + a_3\ i^2 + a_4\ v + a_5\ v^2 + a_6 iv \tag{5.1}$$

Here i is the precipitation intensity (cm/h), v is the visibility level (kilometers), (iv) is the interaction term between precipitation and visibility, and a_1 through a_6 are calibrated model parameters. The results of the regression analysis for the three cities is documented in Table 5.1. Once the inclement weather adjusted parameters are estimated, they can be used to estimate the various microscopic traffic simulation parameters. The remainder of this report describes the models used within various microsimulation packages, and the techniques that could be used to incorporate weather-related factors into these models.

Table 5.1 Regression Analysis Summary Results

	Precipitation	City	n	a_1	a_2	a_3	a_4	a_5	a_6	*P*-val.	R^2_{Adj}	Normality Test		Levene's Variance Test *P*-value
												A^2	*P*-value	
u_f	Rain	Baltimore	32	0.963 (0.000)	-0.033 (0.001)	–	–	–	–	0.001	0.304	0.485	0.211	0.684
		Twin Cities	45	0.980 (0.000)	-0.0274 (0.000)	–	–	–	–	0.000	0.540	0.553	0.146	0.424
		Seattle	43	0.973 (0.000)	-0.0650 (0.000)	0.0240 (0.004)	–	0.0010 (0.044)	–	0.000	0.607	0.336	0.493	0.067
	Snow	Baltimore	8	0.955	–	–	–	–	–	–	–	–	–	–
		Twin Cities	32	0.842 (0.000)	-0.131 (0.002)	–	–	0.0055 (0.000)	–	0.000	0.866	0.456	0.251	0.704
		Aggregated	40	0.838 (0.000)	-0.0908 (0.025)	–	–	0.00597 (0.000)	–	0.000	0.824	0.340	0.482	0.624
u_c	Rain	Baltimore	35	0.920 (0.000)	-0.0560 (0.003)	–	–	–	–	0.003	0.236	0.581	0.120	0.989
		Twin Cities	53	0.928	–	–	–	–	–	–	–	–	–	–
		Seattle	50	0.906	–	–	–	–	–	–	–	–	–	–
	Snow	Baltimore	8	0.955	–	–	–	–	–	–	–	–	–	–
		Twin Cities	41	0.852 (0.000)	–	–	0.0226 (0.000)	–	–	0.000	0.497	–	0.828	0.864
q_c	Rain	Baltimore	35	0.892	–	–	–	–	–	–	–	–	–	–
		Twin Cities	43	0.889	–	–	–	–	–	–	–	–	–	–
		Seattle	49	0.896	–	–	–	–	–	–	–	–	–	–
	Snow	Baltimore	6	0.877 (0.000)	–	–	–	–	–	–	–	–	–	–
		Twin Cities	38	0.794 (0.000)	–	–	–	0.00508 (0.000)	–	0.000	0.480	0.318	0.524	0.859

5.2 TRAFFIC SIMULATION LONGITUDINAL VEHICLE MOTION MODELS

5.2.1 Overview

Longitudinal motion models describe the various movements of vehicles as they move forward along a roadway. Three subcategories of longitudinal motion model are discussed in this report:

1. Car-following models;
2. Deceleration models; and
3. Acceleration models.

Between them they explain the behavior of drivers as they follow in a steady-state mode or as they react to changes in traffic flow downstream.

The traffic flow speed-density relationship forms the basis of these models, and can be explained simply as follows: if a one-kilometer circular track contains five vehicles traveling at 100 km/h, then under steady-state conditions a total of 500 vehicles per hour would be observed passing a specific point along the track.

According to Daganzo it is reasonable to postulate that if traffic conditions on a given road are stationary, there should be a relationship between flow and speed that will be a property of:

1. Road characteristics such as number of lanes, geometry, etc.;
2. Weather conditions; and
3. The population of travelers/vehicles.

This is based on the hypotheses that one can reasonably expect drivers to do the same on average under the same average conditions. The subsections below discuss how various microsimulation models incorporate longitudinal motion factors and how weather factors can be incorporated into the three types of submodels (Ref 17).

5.2.2 Car-Following Models

Over the last few decades, several car-following models have been developed and incorporated within microsimulation software packages. This section describes the characteristics of six of the state-of-practice and state-of-art car-following models, including the Pitt model (CORSIM), Gipps' model (AIMSUN2), Wiedemann74 and 99 models (VISSIM), Fritzsche's model (Paramics), and the Van Aerde model (INTEGRATION). Subsequently in this report, each model is characterized based on its steady-state behavior and procedures are developed to calibrate the model parameters.

The Pitt car-following model that is used in the CORSIM software uses the vehicle spacing between the front bumper of the lead vehicle and front bumper of the following vehicle at time *t* (m) as the independent variable. Forecast variables included are the vehicle spacing when vehicles are completely stopped in a queue (m), *a* the driver sensitivity factor (s), a calibration constant that equals 0.1 if the speed of the following vehicle exceeds the speed of the lead vehicle, otherwise it is set to 0 (km/h), the difference in speed between lead and following vehicle (km/h) at instant $t+\Delta t$, and the speed of the following vehicle at instant *t* (km/h).

The Gipps' model assumes that vehicles travel as close to their desired speed as possible within their constraints of vehicle dynamics.

Here the dependent variable $u_n(t)$ is the speed of vehicle *n* at time *t* (km/h) plus the driver's reaction time. Independent variables include the maximum desired acceleration rate of vehicle *n* (m/s^2), the desired speed of vehicle *n* or the vehicle-specific free-flow speed (km/h); deceleration parameters of vehicle *n* (m/s^2); the actual most severe deceleration rate the vehicle is willing to employ in order to avoid a collision; and the estimated most severe deceleration rate the leader vehicle is willing to employ. Also used are the effective length of vehicle *n*-1 (the actual length plus a safety margin); the spacing between vehicle *n* and *n*-1 at time *t* (m); and the speed of the preceding vehicle in km/h.

In the case of the Wiedemann74 model, the desired vehicle spacing is an interval instead of a single value as was the case with previously mentioned models. Only the boundaries of desired vehicle spacing interval determine the steady-state characteristics of the VISSIM car-following model. The model uses user specified vehicle-specific normally distributed random variables with a default mean values of 0.5 and a standard deviation of 0.15 as well as a series of user-defined calibration parameters. The Wiedemann99 model is a Pipes model and thus is similar to the CORSIM steady-state car-following model.

The Fritzsche's model uses the same modeling concept as the Wiedemann74 car-following model with the vehicle spacing ranging between the desired spacing and the risky spacing. These two boundaries are forecast using the vehicle spacing at jam density, the risky time gap T_r (usually 0.5 s), and the desired time gap (with a recommended value of 1.8 s).

The INTEGRATION car-following model, like the Gipps model, computes the vehicle speed as the minimum of the maximum vehicle speed based on vehicle dynamics and the desired speed based on the Van Aerde model formulation. The microscopic car-following parameters for each software can be calibrated using the adjusted four traffic stream parameters (u_f, u_c, q_c, and k_j), as summarized in Table 5.2. In other words all models that are a function of these four macroscopic parameters are impacted by inclement weather.

Table 5.2 Steady-State Model Calibration

Car-Following Model	Steady-State Calibration
Pitt Model	$c_3 = 3600\left(\frac{1}{q_c} - \frac{1}{k_j u_f}\right)$
Wiedemann 74	$E(BX) = 1000\sqrt{3.6}\sqrt{u_f}\left(\frac{1}{\alpha q_c} - \frac{1}{k_j u_f}\right)$ and $E(EX) = \frac{\frac{k_j u_f}{q_c} - 1}{\frac{k_j u_f}{\alpha q_c} - 1} \simeq \alpha$
Wiedemann 99	$CC0 = \frac{1000}{k_j} - \bar{L}$ and $CC1 = 3600\left(\frac{1}{q_c} - \frac{1}{k_j u_f}\right)$
Gipps	B = b': $T = 2400\left(\frac{1}{q_c} - \frac{1}{k_j u_f}\right)$ b > b': Invalid behavior with a nonconcave car-following relationship b < b': $b = \frac{1}{\left(\frac{1}{b'} + \frac{25920}{k_j u_c^2}\right)}$ and $T = 2.4\left(\frac{1000}{q_c} - \frac{1000}{k_j u_c} - \frac{u_c}{25.92b}\left(1 - \frac{b}{b'}\right)\right)$
Fritzsche	$A_0 = \frac{1000}{k_j}$; $T_D = 3600\left(\frac{1}{q_c} - \frac{1}{k_j u_f}\right)$; and $T_r = 3600\left(\frac{1}{q_c^{\max}} - \frac{1}{k_j u_f}\right)$
Van Aerde	$c_1 = \frac{u_f}{k_j u_c^2}\left(2u_c - u_f\right);\quad c_2 = \frac{u_f}{k_j u_c^2}\left(u_f - u_c\right)^2;\quad c_3 = \left(\frac{1}{q_c} - \frac{u_f}{k_j u_c^2}\right)$

Source: Ref 18.

5.2.3 Deceleration Model Calibration

In quantifying the impact of inclement weather on driver deceleration behavior, data from an infrastructure-based radar and video data collection system were utilized. The system measured a variety of state and kinematics parameters (such as brake status, acceleration level, and velocity) for vehicles at five stop-controlled and three four-way signalized intersections for two months at each location. Data were collected and analyzed with the goal of understanding how drivers approach intersections under various approach speeds and different environmental conditions.

The typical approach used to model vehicle deceleration is based on the assumption that the vehicle decelerates at a constant rate. This rate cannot exceed the maximum rate that is governed by the roadway surface condition.

In addition to adjusting the steady-state car-following behavior, the maximum vehicle deceleration level can be adjusted to reflect wet roadway conditions as:

$$d_{max} = \left(0.5088 - 0.03948i\right)g = \eta_b \mu g \left(1.0 - 0.07759i\right). \tag{5.2}$$

Note that the impact of wet roadway conditions on maximum driver deceleration levels was only quantified using arterial data. It is hypothesized that driver maximum deceleration behavior is similar on freeway roadways given that maximum deceleration levels are only constrained by the coefficient of roadway adhesion and not by the facility type. If deceleration behavior were to be characterized on freeways then additional data would need to be analyzed. Naturalistic driver datasets could provide data for the analysis of maximum driver deceleration levels.

The CORSIM software does not allow for the calibration of vehicle deceleration levels nor does the VISSIM Wiedemann99 model. In the case of the Wiedemann74 model the impact of wet roadway conditions can be captured by equating the maximum deceleration rate (b_{min}) with the maximum possible deceleration rate computed in Equation (5.2) for the specified rain intensity level. Similarly, in the case of the Gipps, Fritzsche, and Van Aerde model parameters can be set equal to the maximum deceleration rate for a specific rain precipitation intensity computed using Equation (5.2).

Table 5.3 Deceleration Model Calibration

Car-Following Model	Deceleration Behavior
Pitt Model	Not possible given that b is fixed at 0.1.
Wiedemann 74	Assume $b_{min} = d_{max}$ in $$b_n(t) = \begin{cases} \frac{1}{2} \cdot \frac{\left[u_n(t) - u_{n-1}(t)\right]^2}{ABX - \left[\Delta x_n(t) - L_{n-1}\right]} + b_{n-1}(t) + b_{\min} \cdot \frac{ABX - \left[\Delta x_n(t) - L_{n-1}\right]}{BX} & s_n(t) \leq \\ \frac{1}{2} \cdot \frac{\left[u_n(t) - u_{n-1}(t)\right]^2}{ABX - \left[\Delta x_n(t) - L_{n-1}\right]} + b_{n-1}(t) & s_n(t) > \end{cases}$$
Wiedemann 99	Not possible.
Gipps	b' = d_{max} and $b = \frac{1}{\left(\frac{1}{b'} + \frac{25920}{k_j u_c^2}\right)}$
Fritzsche	$b_{min} = d_{max}$ amd $u_n(t + \Delta t) = \frac{s_n(t) + \frac{\left(u_{n-1}(t) - u_n(t)\right)^2}{\left\lvert b_{\min}\right\rvert + b_{n-1}(t)} - A_0}{T_r}$
Van Aerde	B = d_{max} and $c_1' = \frac{u_f}{k_j u_c^2}\left(2u_c - u_f\right) + \max\left(\frac{u_n^2(t) - u_{n-1}^2(t)}{2b}, 0\right).$

5.2.4 Acceleration Model Calibration

The modeling of vehicle acceleration can be achieved using a kinematics or a dynamics approach. A kinematics approach, which is used in all simulation software except for the INTEGRATION software, assumes a relationship between vehicle acceleration and speed. This relationship can be assumed to be a linear decaying function of vehicle acceleration as a function of speed or some other form, as will be described in the description of the Gipps model. Alternatively, the dynamics approach considers all forces acting on the vehicle and computes the acceleration from the resultant force. The latter approach is more appropriate because it explicitly accounts for the roadway surface condition.

In the case of the CORSIM, Paramics, and VISSIM software, the modeler can provide a speed-acceleration relationship. The relationship can be derived using the vehicle dynamics models. In the case of the AIMSUN2 software, the desired vehicle acceleration rate can be computed based on the fact that the maximum acceleration occurs as the vehicle speed approaches 0. The maximum sustainable force between the roadway surface and the vehicle tires then becomes the governing factor (F_{max}). Consequently, the desired maximum acceleration rate can be computed as a function of the gravitational acceleration of 9.8066 m/s^2. This methodology relates the maximum desired acceleration to vehicle, roadway, and driver characteristics. Driver characteristics are accounted for using the proportion of the maximum acceleration that the driver is willing to exert. All other terms used are related to the vehicle and roadway characteristics.

In the case of heavy-duty trucks (weight-to-power ratio greater than 30 kg/kW) the maximum acceleration is constrained by the engine tractive force as opposed to the maximum sustainable force between the vehicle tires and roadway surface. Experimentation with various truck data demonstrated that the best fit is obtained for a speed of two km/h.

In the case of the INTEGRATION software the calibration of vehicle acceleration behavior is achieved by changing the coefficient of road adhesion and the rolling coefficient given that the model uses the vehicle dynamics model.

Using vehicle dynamics models it is possible to compute the maximum possible acceleration a vehicle can exert. The coefficients summarized in Table 5.4 are used to adjust the maximum acceleration levels depending on roadway surface conditions. The coefficient of friction is used to adjust the maximum possible acceleration a vehicle can exert while the rolling coefficient is used to adjust the rolling resistance to the vehicle motion.

Table 5.4 Rolling and Friction Coefficient Values Based on Roadway Surface Condition

Pavement Type	Pavement Condition	C_r	Coefficient of Friction
Concrete	Excellent	1.00	0.80
	Good	1.50	0.70
	Poor	2.00	0.60
Asphalt	Good	1.25	0.60
	Fair	1.75	0.50
	Poor	2.25	0.40
Macadam	Good	1.50	0.55
	Fair	2.25	0.45
	Poor	3.75	0.35
Cobbles	Ordinary	5.50	0.50
	Poor	8.50	0.40
Snow	2 inches	2.50	0.20
	4 inches	3.75	0.15
Dirt	Smooth	2.50	0.30
	Sandy	3.75	0.20
Mud		3.75 to 15.0	0.15
Sand	Level soft	6.0 to 15.0	0.15
	Dune	16.0 to 30.0	0.10

Source: Ref 14.

5.2.5 Conclusion

Table 5.5 summarizes the findings with regard to longitudinal vehicle motion models. The feasibility of incorporating weather-related factors is summarized for each of the six microsimulation software and each of the three categories of longitudinal motion models, car-following, acceleration, and deceleration. In general weather-related adjustment factors can be used in these models, although incorporating the acceleration models generally requires a separate calibration of a vehicle dynamics model.

With regards to car-following model calibration all models can be adjusted to capture inclement weather conditions, however apart from the AIMSUN and INTEGRATION software, all software assume that the speed-at-capacity equals the free-flow speed. Consequently, only the AIMSUN2 and INTEGRATION software allow for the adjustment of the speed-at-capacity for inclement weather conditions.

Table 5.5 Feasibility of Incorporating Longitudinal Motion Models into Microsimulation Packages

		Longitudinal Motion		
		Car-Following	**Acceleration**	**Deceleration**
CORSIM	Feasibility	Yes but cannot change speed-at-capacity. Also can only be done for the entire network.	Yes	No
	Data Required	WAFs to compute the free-flow speed and driver sensitivity factor.	Run a vehicle dynamics model first with modified roadway adhesion and rolling resistance coefficients to generate the acceleration versus speed relationship. One major problem is that this is network-specific.	
VISSIM	Feasibility	Yes but cannot change speed-at-capacity. Also can only be done for the entire network.	Yes	Yes
	Data Required	WAFs to compute the free-flow speed and saturation flow rate. These can then be used to modify the BX and EX parameters or the CC0 and CC1 parameters.	Run a vehicle dynamics model first with modified roadway adhesion and rolling resistance coefficients to generate the acceleration versus speed relationship. One major problem is that this is network-specific.	Use deceleration adjustment factor.
Paramics	Feasibility	Yes but cannot change speed-at-capacity. Also can only be done for the entire network.	Yes	Yes
	Data Required	WAFs to compute the free-flow speed and saturation flow rate. These can then be used to modify the A_0, T_D, and T_r parameters.	Run a vehicle dynamics model first with modified roadway adhesion and rolling resistance coefficients to generate the acceleration versus speed relationship. One major problem is that this is network-specific.	Use deceleration adjustment factor.
AIMSUN2	Feasibility	Yes	Yes	Yes
	Data Required	WAFs used to compute the free-flow speed, saturation flow rate, and speed-at-capacity. These are then used to modify the deceleration rate b) and reaction time (T).	Run a vehicle dynamics model first with modified roadway adhesion and rolling resistance coefficients to generate the acceleration versus speed relationship. One major problem is that this is network-specific.	Use deceleration adjustment factor.
INTEGRATION	Feasibility	Yes. Adjust free-flow speed, speed-at-capacity, and saturation flow rate using weather adjustment factors.	Adjust roadway coefficient of adhesion and rolling resistance coefficients.	No. Currently the deceleration level is fixed. This could easily be changed.
	Data Required	Rain intensity and WAFs.	Coefficient of roadway adhesion and rolling resistance coefficients.	Use deceleration adjustment factor.

With regards to acceleration model calibration, only the INTEGRATION model allows for the incorporation of the roadway surface conditions directly into the model. Alternatively, other software require that a vehicle dynamics model be executed first considering adjusted roadway surface conditions and then inputting the acceleration versus speed relationship derived from the vehicle dynamics model into these software.

Finally, the calibration of deceleration characteristics can be made to all software except the CORSIM and INTEGRATION software at this stage.

5.3 LANE-CHANGING MODELING

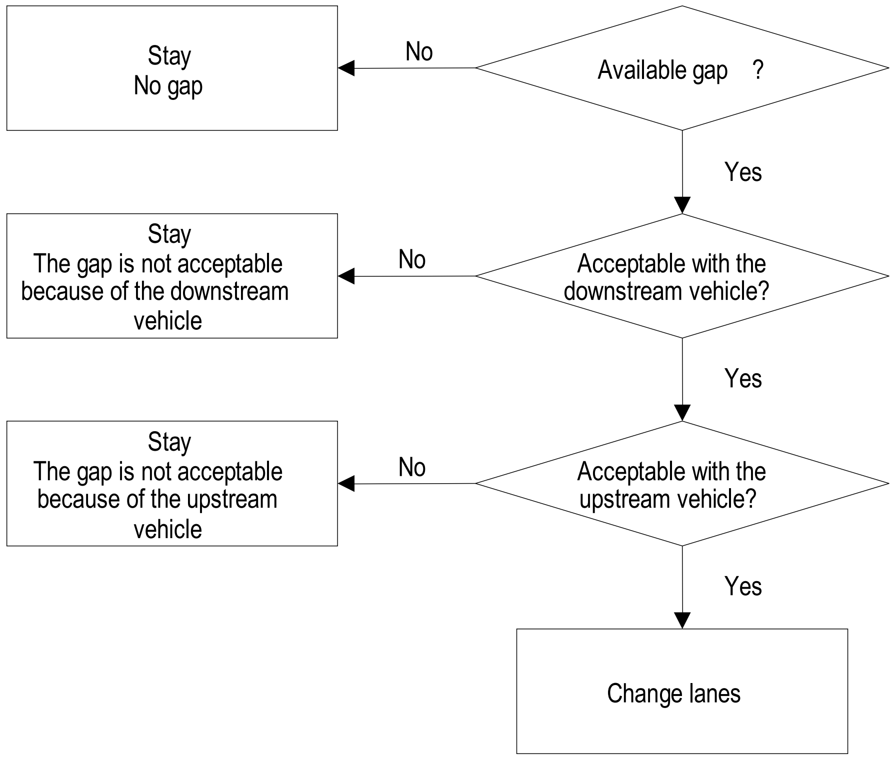
Different types of models are used to describe lane-changing behavior. These models can be categorized as: 1) simulation models; 2) mathematical models; and 3) empirical models. These models were discussed in Section 4.4.3.

The remainder of this section provides several illustrations of how lane-changing behavior is incorporated into various microsimulation packages. The CORSIM and Paramics models logic are not described because literature describing the logic were not available.

5.3.1 The AIMSUN Software

The AIMSUN software uses the Gipps lane-changing model to approximate the driver's lane-changing behavior. The model involves a set of decisions. First, the model determines whether or not a lane change is necessary. Second, an answer is made if it is desirable to change lanes based on the estimated improvement in the traffic conditions. Finally, the model determines the feasibility of changing lanes. Specifically, the lane-changing feasibility is determined by answering three questions, as illustrated in Figure 5.1 (Ref 19).

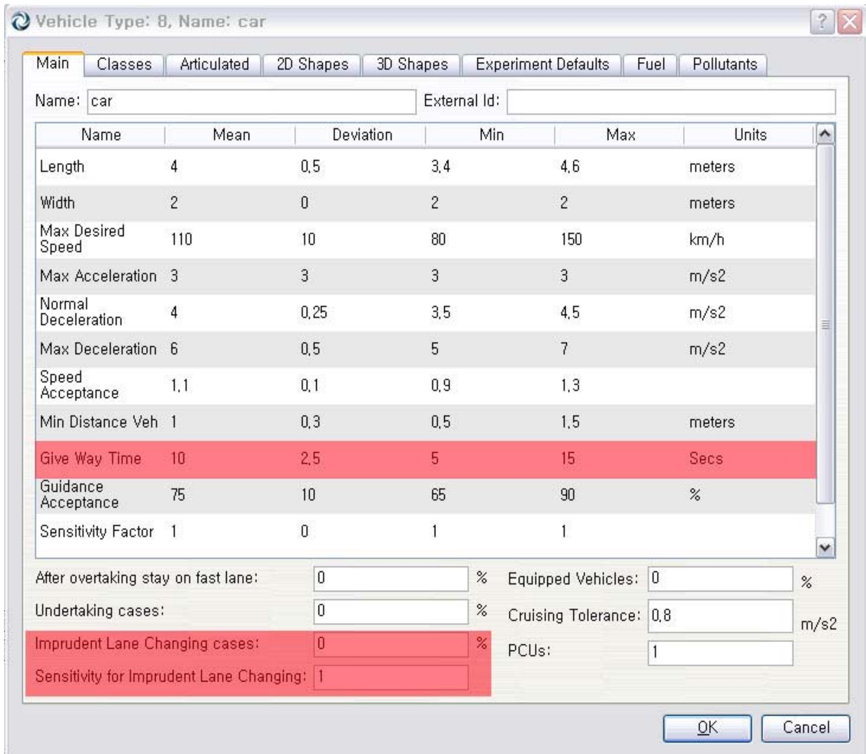
Figure 5.1 Gap Acceptance Model within AIMSUN Lane-Changing Model

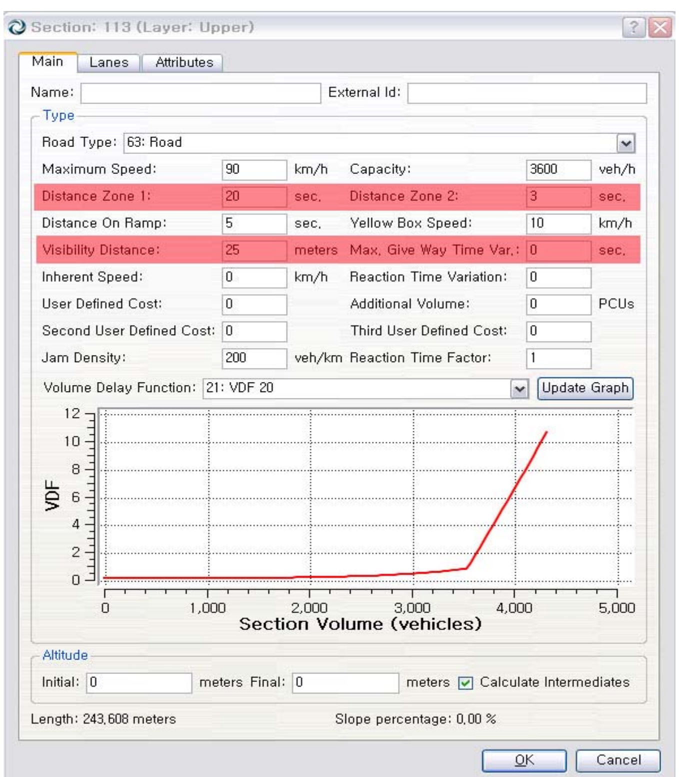


For the calibration of the gap acceptance behavior, the user can define relevant vehicle modeling and local parameters. The vehicle parameters include the Maximum Give Way Time distribution (mean, deviation, min, max), Imprudence Lane-Changing Cases, and Sensitivity for Imprudence Lane-Changing by vehicle type as illustrated in Figure 5.2.

Maximum Give Way Time is used to set a temporal threshold after which the accepted gap size is reduced. In other words, if a vehicle has been waiting more than a specified give way time to change lanes, it will become more aggressive and accept a reduced gap. It is not clear how this behavior is modeled. The Imprudence Lane-Changing Cases parameter defines the percentage of vehicles that accept an unsafe gap. The Sensitivity for Imprudence Lane-Changing parameter is used to determine the deceleration of the upstream vehicle to apply an Imprudence Lane Changing (Ref 20).

Figure 5.2 Vehicle Modeling and Local Parameters





The local parameters include Visibility Distance, Distance Zone1, Distance Zone2, and Maximum Give Way Time Variability, as illustrated Figure 5.2. The Zone1, Zone2, and Zone3 parameters within a link are defined to achieve a more realistic lane-changing behavior by means of introducing variations in the driver's acceptance of the gap as a function of the distance to the end of the link (next turning point) (Ref 19).

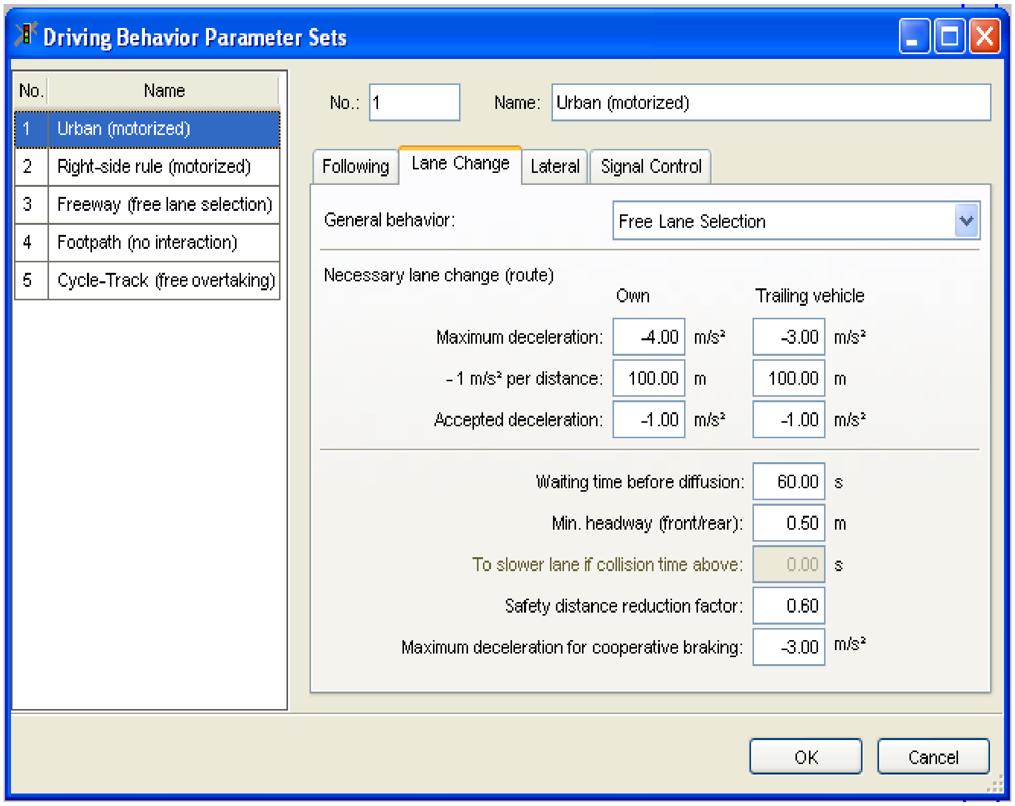
5.3.2 The VISSIM Software

The VISSIM software models two types of lane-change maneuvers, namely necessary (mandatory) and free (discretionary) lane changes. As the names imply, the necessary lane change is made to follow the desired route while the free lane change is made to increase the vehicle's speed. In both cases, the first step for a driver to change lanes is to find a suitable gap. In the VISSIM software, there is no way for the user to define the suitable gap size. In case of a necessary lane change, however, the aggressiveness of lane change of a specific driving behavior can be defined with a set of parameters: Maximum Deceleration, – one foot/s^2 per distance, and Accepted Deceleration for the vehicle and the trailing vehicle on the new lane, as illustrated in Figure 5.3. In the Lane Change tab, there are five additional parameters: Waiting Time before Diffusion, Minimum Headway (front/rear), To Slower Lane If Collision Time, Safety Distance Reduction Factor, and Maximum Deceleration for Cooperative Braking (Ref 20).

These variables are defined as follows:

- **Waiting Time before Diffusion –** The maximum amount of time that a vehicle can wait at the emergency stop position waiting for a gap to change lanes in order to stay on its route;
- **Minimum Headway (Front/Rear) –** The minimum distance to the vehicle in front that must be available for a lane change in standstill condition;
- **To Slower Lane If Collision Time –** The minimum time headway towards the next vehicle on the slow lane so that a vehicle on the fast lane changes to the slower lane;
- **Safety Distance Reduction Factor –** During any lane change, the resulting shorter safety distance is calculated as follows: original safety distance x reduction factor; and
- **Maximum Deceleration –** The maximum deceleration the vehicle would use in case of cooperative braking thus allowing a lane-changing vehicle to change into its own lane.

Figure 5.3 VISSIM Lane-Change Parameters



In case of a free lane change, the desired safety distance of the trailing vehicle on the new lane is checked to find a suitable gap, which means that the free lane changes will be effected by the changes in the parameters for the desired safety distance. Consequently, the lane-changing model is closely related to the car-following model (Ref 20).

5.3.3 The INTEGRATION Software

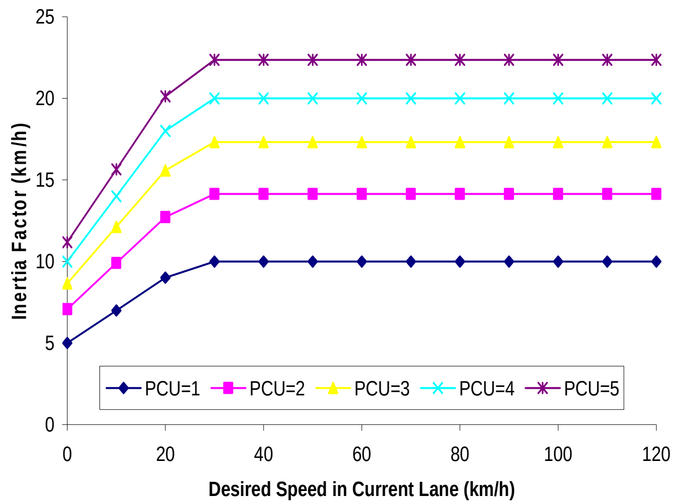
The lane-changing logic within the INTEGRATION software, as the case with the VISSIM software, considers both mandatory and discretionary lane changes. Mandatory lane-changing takes place when the current lane ceases to be a feasible option, and the driver must shift to another lane in order to leave the road or to avoid a roadway exit. Discretionary lane changing occurs when the adjacent lane is perceived to provide for better driving conditions. This lane-changing logic incorporates a gap acceptance process, where the size of an acceptable gap in the adjacent lane is a function of the vehicle's speed, distance to the point where the lane change should be completed, and the time spent by an individual vehicle searching for a gap.

The INTEGRATION model computes the vehicle's desired speed every decisecond based on the distance headway and speed differential between the leading and following vehicles. In order to determine whether a discretionary lane change should be made, the perceived speeds in the current lane, the adjacent lane to the left, and the adjacent lane to the right are compared every second. In addition, all lanes are scanned every five seconds in order to identify any potential gaps across multiple lanes and the movement of vehicles to a High-Occupancy Vehicle (HOV) lane. The INTEGRATION model considers a prespecified bias for a vehicle to remain in the lane in which it already is traveling by adding an inertia factor to the vehicle's desired speed when computing its perceived speed. The use of such a bias factor reduces the number of unnecessary lane changes by increasing the attractiveness of the current lane.

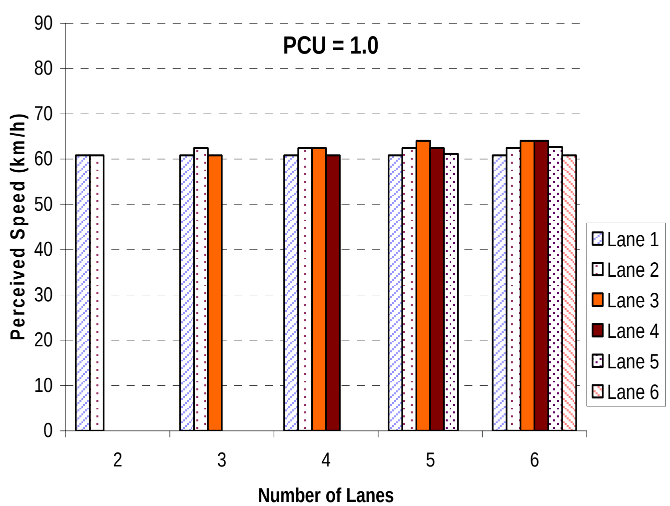
Figure 5.4 illustrates the INTEGRATION default parameters and the variation in the lane inertia factor as a function of the lane desired speed, as computed from the car-following model, and the vehicle length Passenger Car Unit (PCU) equivalency. The figure clearly demonstrates that the inertia factor increases as the desired speed increases through the use of the relative factor (f_3), which encourages vehicles to make more lane changes at low speeds in order to minimize queue lengths at a signalized intersection. Furthermore, the inertia factor increases as the vehicle PCU increases. The use of the vehicle length equivalency factor within the inertia factor ensures that trucks make less lane changes than passenger cars.

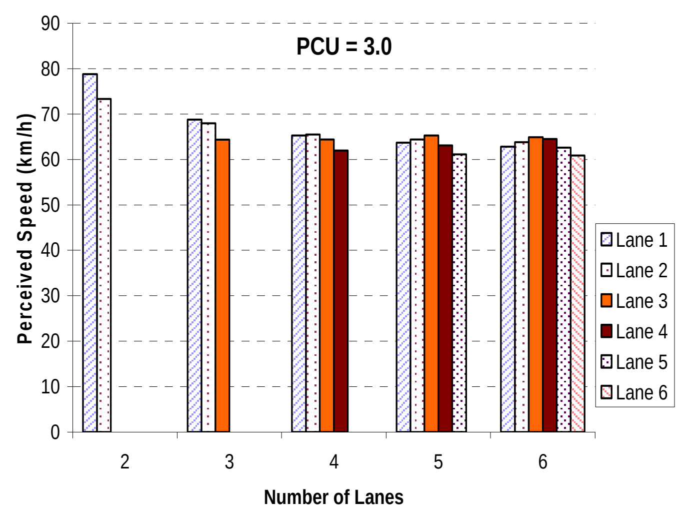
In addition, the INTEGRATION 2.30 model incorporates a bias towards travel in specific lanes depending on the number of lanes on the roadway when vehicles travel outside the influence area of merge and diverge sections. Specifically, the model biases passenger cars to travel towards the middle lanes for roadways with three or more lanes, as demonstrated in Figure 5.4. This bias is achieved by altering the perceived speed in a specific lane using a formula which attempts to achieve field observed traffic volume distributions across roadway lanes, as was characterized in the literature. In addition, the model biases trucks towards use of the shoulder lane through the Passenger Car Unit (PCU) vehicle length equivalency factor, as demonstrated in Figure 5.4.

Figure 5.4 INTEGRATION Default Lane-Bias Features



f3	0.2
f4	5
f5	10
f7	0.01
f8	1

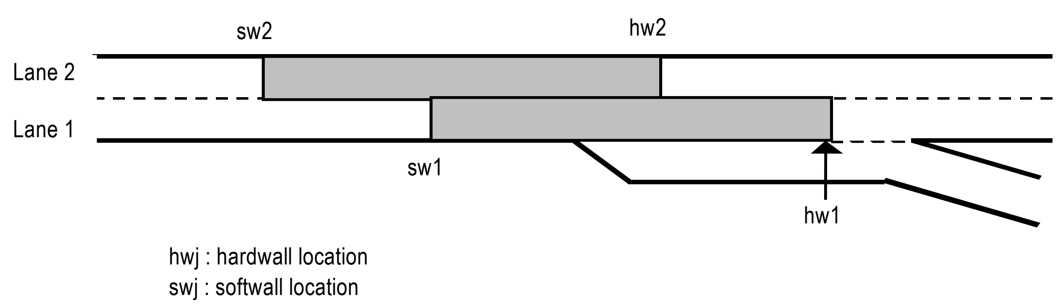




It should be noted that the INTEGRATION 2.30 software allows users to override the default lane-bias parameters using the optional "lanebias.dat" input file. Specifically, the user can specify the degree of attractiveness of a lane using a divisive speed bias factor. For example, if the user specifies a factor of 3.0 the perceived speed on all lanes other than the biased lane is computed as one-third the desired speed, which is computed using the car-following logic. The "lanebias.dat" file allows the user to identify link-specific bias factors that are only effective on the links that are coded in the optional file. Once the vehicle leaves the link the default bias factors become effective. Consequently, if the user wants to maintain a user-specified bias over a number of links, a separate entry is required for each of the links. These bias factors could be useful in assessment of adverse weather impacts, since it can be hypothesized that lane selection will differ under these conditions. Additional research is needed to confirm this is the case.

In situations where a trip destination imposes a constraint on vehicle movement, for example, exiting vehicles at a ramp-freeway diverge section; mandatory lane changes are performed to ensure that vehicles maintain lane connectivity at the end of each link. This lane connectivity at any diverge or merge point is computed internal to the model rather than explicitly coding this as an input to the model. In order to briefly explain the mechanism of the mandatory lane-changing logic within INTEGRATION, a simple configuration of a freeway diverge section in the proximity of an exit ramp is considered for this purpose, as shown in Figure 5.5.

Figure 5.5 Hardwall and Softwall Locations at a Sample Diverge Section



Prior to reaching the physical diverge point, the obligatory lane-changing logic in INTEGRATION assigns two imaginary boundaries upstream of the diverge gore. The first boundary, located farther upstream, is denoted as "softwall"; while the second boundary is denoted as "hardwall" and is located closer to the physical diverge point. While the hardwall indicates the location where exiting vehicles are unable to proceed closer to the diverge section on the original lane and thus must abandon the lane due to lane discontinuity downstream; the softwall defines the location where the driver recognizes the need to change lanes in order to exit at a diverge section. The distance between these two boundaries represents a transition from the absolute discretionary nature to the absolute mandatory nature for the vehicle under consideration.

In order to ensure the smooth transition of flows from one lane to the next, the mandatory lane-changing logic within INTEGRATION has been made highly stochastic rather than purely deterministic. This is reflected by the significant variation in the locations of the softwalls and the hardwalls upstream of the diverge gore. Within INTEGRATION, the mean locations of the softwalls are at a distance of $100n$ times the jam density distance headway upstream of the diverge gore, where n is the minimum number of lane changes required to complete the maneuver. Likewise, the mean locations of the hardwalls are at a distance of $10n$ times the jam density distance headway back from the point of diverge, where n is as defined earlier. This implies that some very cautious drivers will strive to be in the rightmost lane a considerable distance upstream of the diverge gore. The locations of these imaginary boundaries were set based on engineering judgment and extensive testing of the model for different traffic and roadway conditions. It should be noted, however, that the user can alter the default lane-change parameters that are incorporated within the INTEGRATION software by using an optional input file named "lanechange.dat." This optional file provides the user with some degree of control over the lane-changing behavior within the simulation model using global customization parameters. It is likely that the softwalls and possibly the hardwalls would move further upstream during adverse weather conditions, as drivers become more cautious. Use of a modified "lanechange.dat" file would enable a user to incorporate different parameters for lane-changing during adverse weather.

In addition, the INTEGRATION model considers a mean default lane-change duration of two seconds that again can be altered by the modeler via the "lanechange.dat" file. This assumption also could be modified on the possibility that drivers would take longer to change lanes during adverse weather. Currently, the model does not reduce the lane-change duration depending on the number of lane changes that the driver has to make nor does it alter the duration depending on the urgency of the lane-changing maneuver. Further research is required to attempt to characterize lane-changing behavior as a function of the number of lane-change maneuvers, the urgency of the lane-change maneuver, roadway, and visibility conditions and the level of congestion on the roadway.

A commonly observed phenomenon at merge and weaving sections is the movement of mainline vehicles from the shoulder lane to the middle and median lanes in order to avoid any interaction with merging vehicles. This behavior can be captured within the INTEGRATION software using the optional "lanebias.dat" file that was described earlier. Specifically, the use of a factor of 2.0, which results in a perceived speed that is half the actual speed on the surrounding lanes provides a good level of movement of vehicles from the shoulder lane to other lanes. Specifically, a factor of 2.0 entices vehicles to use the desired lane at low volumes; however, it has a minor effect at high volumes. As was the case with the soft and hardwalls the location at which vehicles respond to the specified bias is varied randomly across the different vehicles in order to ensure that not all lane changing occurs at the same location.

5.3.4 Conclusion

Given that the project was not able to gather any data on lane-changing behavior it is not possible to capture the impact on inclement weather on lane-changing behavior at this point. It is the conclusion of the research staff that lane-changing behavior can be incorporated into all of the reviewed simulation packages by adjusting the gap acceptance parameters. A brief description of how the parameters can be altered and what data are required to do so is provided in Table 5.6.

Table 5.6 Incorporation of Weather-Related Factors into Lane-Changing Models

		Gap Acceptance
CORSIM	Feasibility	Could not find material on the modeling approach.
	Data Required	–
VISSIM	Feasibility	Yes by adjusting the safety distance adjustment factor and the maximum deceleration level.
	Data Required	Use the steady-state car-following models to adjust the safety distance and the roadway surface condition to adjust the deceleration levels.
Paramics	Feasibility	Could not find material on the modeling approach.
	Data Required	–
AIMSUN2	Feasibility	Yes by adjusting the visibility distance and the maximum give way time variability.
	Data Required	Data need to be gathered to characterize how the maximum give way time varies as a function of inclement weather.
INTEGRATION	Feasibility	Yes by the lane-change duration and the acceptable gap using the adjusted steady-state car-following model spacing.
	Data Required	Data need to be gathered to characterize how lane-change durations vary as a function of inclement weather and how gap acceptance behavior changes as a function of inclement weather.

5.4 Gap Acceptance Models

The research conducted for this project from field observations and data analysis, as documented in Section 4.5, showed that in general an increase in waiting time to accept a gap causes drivers to become more aggressive and willing to accept smaller gaps. Therefore the critical gap value and follow up time decrease. On the other hand, increasing rain intensity may contribute to significant increases in the critical gap as well as follow-up time; because drivers need more response time to decide to accept the available gap.

5.4.1 Gap Acceptance Model Summary

The remainder of this section discusses the incorporation of gap acceptance behavior into several microsimulation packages. The gap acceptance behavior for the CORSIM and Paramics models are not presented here because the researchers did not have access to information describing these procedures. Figure 5.6 shows the relationship of gap acceptance to both waiting time and rain intensity. Results were included for both the first and second lanes. The first two models produced similar results while the third indicated a significant difference between the first and second lane for both waiting time and rain intensity.

5.4.2 The AIMSUN Software

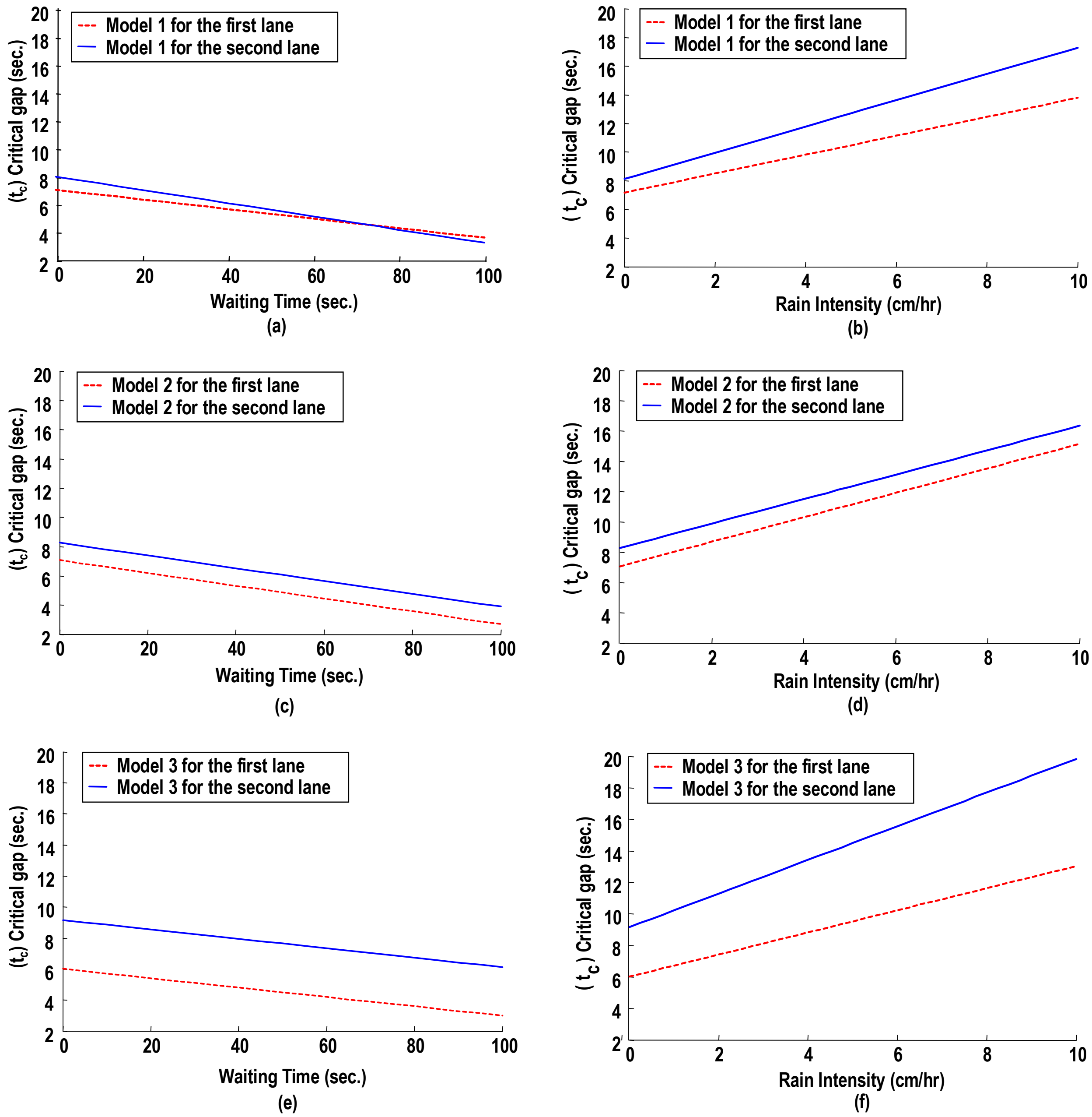
The AIMSUN software models gap acceptance behavior by determining whether a lower-priority vehicle (opposed vehicle) can cross the path of a higher-priority vehicle without resulting in a collision. The parameters used in gap acceptance are similar to those in lane-changing behavior and are not discussed further. The most important parameters among them are the acceleration rate (calibrated using the procedures described earlier), maximum give way time and visibility distance. Specifically, if the travel time for a lower-priority vehicle to cross the theoretical collision point (TCP) distance is less than the travel time for a higher-priority vehicle to reach TCP, the lower-priority vehicle accelerates and crosses. Otherwise, the lower-priority vehicle decelerates and stops to give way (Ref 21).

5.4.3 The VISSIM Software

The VISSIM software provides the user two ways to define gap acceptance behaviors locally. In other words, the user can define a rule to assign the right-of-way for conflicting movements and to specify a minimum gap size at any location in the network.

The first method is to define a Priority Rule that consists of a stop line and a conflict marker or more. The stop line is defined as the location where lower-priority vehicles wait until a suitable gap time or enough distance headway is available. The conflict marker is defined at the location where the user wants to check the gap time and the headway. Therefore, the minimum gap time and the minimum distance headway should be defined at each of the conflict markers as illustrated in Figure 5.7. The minimum gap time refers to free-flow traffic.

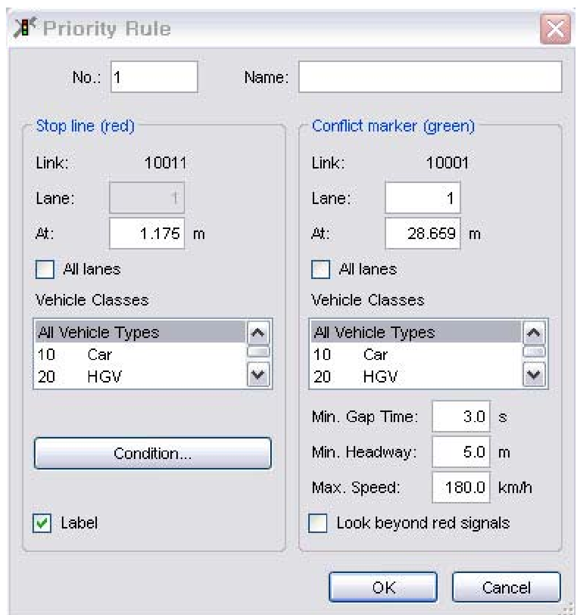
Figure 5.6 Effect of Waiting Time and Rain Intensity on Critical Gap Value for Different Models

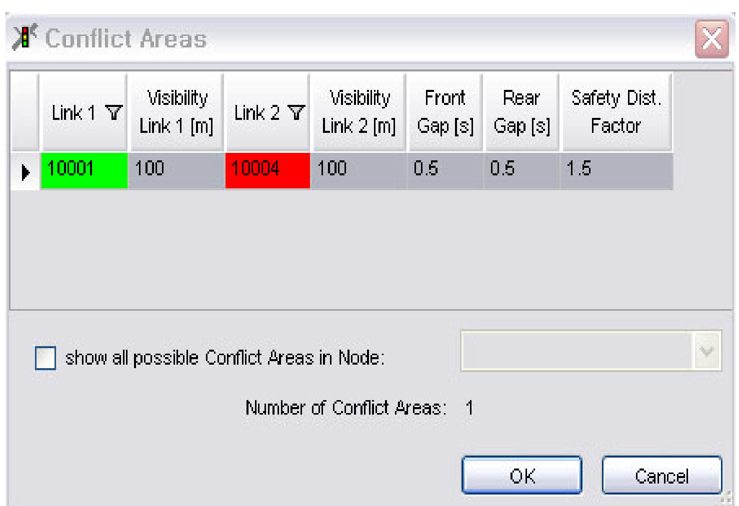


conditions on the higher-priority road while the minimum distance headway reflects the vehicle spacing for slow moving or queuing traffic (Ref 22).

The second method is to define a conflict area where conflicts exist. For the definition of the conflict area, the priority conditions of the conflict, Visibility of the links, Front Gap, Rear Gap, and Safety Distance Factor are used. The priority of the conflict can be defined by selecting the options from the screen, as illustrated in Figure 5.7. In the figure, the green indicates the main road (right-of-way) while the red indicates the minor road. The Visibility is the maximum distance that a vehicle approaching can see other vehicles on the opposing link. The Front Gap is the minimum gap time between the rear end of a higher-priority vehicle and the front end of a lower-priority vehicle. The Rear Gap is the minimum gap time between the rear end of a lower-priority vehicle and the front end of a higher-priority vehicle. Finally, the Safety Distance Factor is a scale factor that is multiplied with the normal desired safety distance of a higher-priority vehicle. The scaled distance is used to determine the minimum headway for a lower-priority vehicle trying to merge in the main road (Ref 22).

Figure 5.7 VISSIM Priority Rules and Conflict Areas





5.4.4 The INTEGRATION Software

In the case of the INTEGRATION software the concept of a driver-specific stochastic critical gap is modeled considering either a normal or lognormal distribution of gap acceptance behavior. Gaps that exceed the driver-specific critical gap are accepted while those that are less than the driver-specific critical gap are rejected. The model also considers the impact of wait time on the critical gap by considering a linear decay function in the critical gap over time. The user can calibrate three intersection-specific gap acceptance parameters, including: a) the mean critical gap; b) the standard deviation in the critical gap; and c) the critical gap acceptance decay parameter. The critical gap also is adjusted for the type of movement, the number of lanes to travel to the conflict point, and the type of intersection. For example the critical gap for a left turn movement is 0.5 s longer than the base through movement. Alternatively, the critical gap for a right turn movement is 0.5 s shorter than the through movement critical gap. Furthermore, the critical gap is increased by 0.5 s for each additional lane of travel. These parameter values are consistent with the HCM and AASHTO Green Book procedures.

5.4.5 Conclusion

Table 5.7 summarizes the findings with regard to the incorporation of gap acceptance models into microsimulation packages. PARAMICS was not evaluated as part of this analysis due to limitations of available documentation. Adjustments for adverse weather are possible in VISSIM, PARAMICS, and AIMSUN2. AIMSUN2 requires calibration of a vehicle dynamics model, while the other two packages can accommodate the type of gap acceptance model developed for this project.

Table 5.7 Incorporation of Weather-Related Factors into Gap Acceptance Models

		Gap Acceptance
CORSIM	Feasibility	By changing the default parameters.
	Data Required	Use the gap models that are being developed to adjust the gap acceptance parameters.
VISSIM	Feasibility	Yes by adjusting the visibility distance, the front gap, rear gap, and safety distance factor.
	Data Required	Use the gap models that are being developed to adjust the gap acceptance parameters.
Paramics	Feasibility	Not reviewed.
	Data Required	–
AIMSUN2	Feasibility	Yes by adjusting the acceleration level, the maximum give way time, and visibility distance.
	Data Required	Adjust the maximum acceleration using a vehicle dynamics model with adjusted wet pavement parameters. It is not clear how the give way time can be adjusted.
INTEGRATION	Feasibility	Yes by adjusting the critical gap size, distribution, and effect of wait time.
	Data Required	Use the gap models that are being developed to adjust the gap acceptance parameters.

6.0 Conclusions and Recommendations

This report has documented recent and current research activities in evaluating the state of microscopic analysis of adverse weather on traffic flow. Existing literature and data sets have been reviewed and evaluated. The major goal of the analysis conducted for this project was to establish techniques and parameters for incorporating the impact of adverse weather into existing microsimulation models. The key questions addressed were:

1. Are there datasets that have adequate quality and quantity of data to estimate parameters with reasonable confidence?
2. Can the microsimulation models as currently structured be modified to accommodate the impacts of adverse weather?

Detailed conclusions regarding individual models and software packages are provided in Section 5.0 but are summarized briefly here:

- Three categories of **Longitudinal motion models** are covered in this research; acceleration, deceleration and car-following. In general weather-related adjustment factors can be used in these models, although incorporating the **acceleration models** generally requires a separate calibration of a vehicle dynamics model. These models can be relatively demanding in terms of data requirements, with information required on both roadway surface and vehicle type. **Deceleration models** were calibrated using arterial data only. Weather-related factors can be incorporated into

  Research indicated all **car-following models** can be adjusted to capture inclement weather conditions, however apart from the AIMSUN2 and INTEGRATION software, all software packages assume that the speed-at-capacity equals the free-flow speed. Consequently, only the AIMSUN2 and INTEGRATION software allow for the adjustment of the speed-at-capacity for inclement weather conditions, an important capability in evaluating adverse weather impacts.

- The project was not able to gather any data for use in estimating **lane-changing models**. Therefore, it was not possible to capture the impact on inclement weather on lane-changing behavior at this point. It is the conclusion of the research staff that lane-changing behavior can be incorporated into all of the reviewed simulation packages by adjusting the gap acceptance parameters. A brief description of how the parameters can be altered and what data are required to do so is provided in Table 5.6.

- **Gap acceptance models** were the third set of models included in the project. Data utilized for the analysis came from three intersections in the Blacksburg, VA region that were fully equipped with detection, surveillance, and environmental sensor station (ESS) equipment. The research conducted for this project from field observations and data analysis, as documented in Section 4.5, showed that in general an increase in waiting time to accept a gap causes drivers to become more aggressive and willing to accept smaller gaps. Therefore the critical gap value and follow up time decrease. On the other hand, increasing rain intensity may contribute to significant increases in the critical gap as well as follow-up time; because drivers need more response time to decide to accept the available gap.

  Adequate information was available for four microsimulation packages to determine whether weather-related gap acceptance parameters could be incorporated. Research found that the models developed for this research effort could be incorporated although in the AIMSUM2 software, a vehicle dynamics model is required as well.

The research clearly showed that additional analysis is required before these models can be incorporated into microsimulation packages and the outputs used for weather-responsive traffic management. Recommendations for additional research include:

- Utilize car-following data from Hokkaido University in Japan to characterize driver deceleration, acceleration, and car-following behavior under icy conditions;
- Investigate the availability of additional datasets for use in longitudinal modeling;
- Identify datasets for use in developing weather-related parameters for lane-changing models. If adequate datasets cannot be found, develop requirements for primary data collection effort;
- Identify datasets for use in developing gap acceptance parameters for freeways. If adequate datasets cannot be found develop requirements for primary data collection effort;
- Develop strategy for collecting and maintaining vehicle dynamics data for use in adjusting longitudinal models;
- Identify additional datasets for evaluating driver behavior in snow and ice conditions. Datasets have been identified from Minnesota and Japan but additional primary data collection is required to assess snow and ice conditions for all three model categories.
- Consider executing simulation scenarios to characterize the impact of inclement weather on system performance for different network types and different levels of congestion. The study or studies would consider isolated signalized intersections, coordinated arterials with small block lengths where

queues could spillback to upstream traffic signals, and coordinated arterials with long block sizes. Other scenarios also could consider the impact of inclement weather when a dedicated left-turn pocket lane is provided versus when it is not provided. Different opposing flows and levels of congestion will be considered to quantify the potential network-wide impacts of inclement weather.

- Consider conducting outreach to microsimulation vendors to coordinate Road Weather Management Program activities with ongoing research. This could take the form of a meeting/conference or a series of meetings with individual vendors.

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