

ABSTRACT

Title of Thesis: TOWARDS MODELING DRIVER BEHAVIOR UNDER
EXTREME CONDITIONS

Degree Candidate: Samer Hani Hamdar

Degree and year: Masters of Science, 2004

Thesis directed by: Professor Hani S. Mahmassani
Department of Civil and Environmental Engineering

The purpose of this study is to investigate the representation of driver behavior under extreme conditions, towards development of a micro-simulation modeling framework of traffic flow to support evaluation of management strategies and measures in emergency situations. To accomplish this objective, particular attention is given to understanding and representing so-called “panic behavior” of individuals and how this behavior may be translated into driver actions. Related background from psychology and sociology is examined to provide proper framing and a better understanding of the manifestation and implications of panic for driver behavior.

Following a systematic review and synthesis of previous traffic models, and an assessment of their suitability and limitations vis a vis representation of driver behavior under extreme conditions, a model is selected as a starting point for modification towards the micro-simulation of traffic flow under such conditions. The model is based on Gipps’

(1981) Car-Following Model, which is combined with a simple representation of the lane changing process. The modification seeks to capture the differences in driving patterns anticipated under certain extreme conditions, and to assess these differences with respect to other traffic models. To evaluate the proposed modification, a prototype implementation is proposed for the micro-simulation of traffic flow on a stretch of highway with simplified geometric features. The vehicle trajectories and aggregate traffic properties, such as volumes and densities, are evaluated with respect to different scenarios and population characteristics, such as the distribution of desired velocities across drivers, through a sensitivity analysis.

**TOWARDS MODELING DRIVER BEHAVIOR UNDER
EXTREME CONDITIONS**

by

Samer Hani Hamdar

Thesis submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Master of Science
2004

Advisory Committee:

Professor Hani S. Mahmassani, Chair
Professor Gang-Len Chang
Professor Elise Miller-Hooks

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Dedicated to my family in Lebanon

ACKNOWLEDGEMENTS

I would like to thank my parents Zeinab and Hani Hamdar, my sister Amal, and my brother Oussama for their continuous support through my graduate experience.

I would like to thank also my colleagues at the University of Maryland at College Park. They were my second family while being away from home. They gave me their technical advice, their support, and above all, their friendship.

Finally, my very special thanks go to my advisor Dr. Hani Mahmassani. He was my guide who always encouraged me to give my best in this new research world.

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LIST OF ABBREVIATIONS

3. CA: Cellular Automata
2. DLC: Discretionary Lane Changing
2. DSM-VI: Diagnostic and Statistical Manual of Mental Disorders – VI
3. FHWA: Federal Highway Administration
4. GHR models: Gaziz-Herman-Rothery Models
5. GM: General Motors
6. HCM: Highway Capacity Manual
7. IDM: Intelligent Driver Model
8. MLC: Mandatory Lane Changing
9. NGSIM: Next Generation Simulation
10. TWLTLs: Two-Way Left-Turn Lanes

CHAPTER 1: EXTREME CONDITIONS

1.1. Introduction

Recent increases in the frequency of both man-made and natural disasters have required driver and traveler behavior models to better account for the effects of extreme dynamic conditions in addition to normal static conditions. Man-made disasters and emergencies, such as terrorist activities, wild fires, and hazardous spills, occur due to human activity, while natural disasters, such as floods and hurricanes, occur without direct human intervention. The effects of extreme conditions are not exclusive to one domain of study, but have implications in a wide range of disciplines such as the biological and environmental sciences, psychology, urban and regional studies, and engineering. In transportation analysis, modeling and understanding driver behavior under extreme conditions is a relatively new concept and has received only limited attention, and has been insufficiently addressed in past research.

A similar and related line of research involving the escape behavior of individuals in panic situations has been addressed by several researchers. Particularly notable in this regard is the work of Helbing (2000), which describes a simulation of the escape panic behavior of individuals in a given room with exits. These individuals were conceptualized and modeled as a “self-driven many-particle system,” with each particle having both physical and socio-psychological attributes. A generalized force model was adopted to describe particle or individual movement. One difference between the crowd evacuation context and

vehicular movement is that constraints must be imposed on the direction of movement in the latter.

In this chapter, extreme conditions are defined and classified into different categories. This study focuses on extreme conditions that may cause panic behavior among drivers. Psychologists have no consensus on the exact definition of “panic”, and in most transportation studies involving panic behavior, an operational definition of panic is typically missing (Helbing 2000). In somewhat general terms, panic is associated with the uncoordinated motion of crowds. The next section discusses panic from a socio-psychological standpoint, in order to set the stage for defining panic behavior in the context of traffic and transportation.

The objective of this thesis is to represent driver behavior under extreme conditions by constructing a micro-simulation model that aims to capture how panic behavior translates into driving actions. For that purpose, the following section presents a classification scheme for extreme conditions. Section 1.3 briefly presents the psychological and social background of “panic” so that it can be related to the traffic characteristics and placed in the context of transportation in Section 1.4. Section 1.5 specifies the research objectives and the approach necessary to accomplish them.

1.2. Classification of Extreme Conditions

As mentioned earlier, “extreme conditions” vary in type and magnitude, and can have different effects on transportation systems and their users. Extreme conditions result from events that can be classified as either human-caused or

naturally occurring. Although these two categories may have some similarities, they also differ in terms of their degree of urgency, their predictability, and the extent to which they may be prevented or otherwise controlled. Naturally occurring extreme conditions include weather conditions and other natural disasters. Accidents, hazardous material releases, terrorist acts, and war are considered human-caused extreme conditions. Additional examples of each category or type of extreme conditions are given in Tables 1.1 and 1.2.

Nature-Caused Extreme Conditions	
Weather	Extreme Heat
	Extreme Cold
	Heavy Rain
	Heavy Snow
	Hurricanes
	Tornados
	Typhoons
Other Natural Disasters	Floods
	Earthquakes
	Volcano Eruptions
	Fires
Others (Tsunami Waves, Meteorites ...etc)	

Human-Caused Extreme Conditions	
Accidents	
Hazardous Materials Spills	Physical Materials (Oil: Slippery)
	Chemical Materials
	Biological Materials
	Nuclear Materials (Dust, Wastes ...etc)
Terrorist Acts	Involving above Hazardous Materials
	Bombing
	Other Disruptions (Fire, Electricity Cut, ...etc)
War Conditions	

Tables 1.1 and 1.2: A Classification Scheme for Nature-Caused (left) and Human-Caused (right) Extreme Conditions

Note that hurricanes, tornados, floods and typhoons are considered natural disasters as well as weather conditions. Additionally, war conditions can be seen as a combination of different sources of extreme conditions, such as bombing,

accidents, or nuclear material spills. Furthermore, certain conditions are undoubtedly more “extreme” than others; for example, extreme heat, extreme cold, heavy rain, and heavy snow may not pose the same level of threat as some of the other extreme conditions mentioned. Given this characterization, extreme conditions can be broadly defined as any abnormal high-impact conditions affecting the transportation system and its users. The degree to which conditions are deemed normal rather than extreme, such as weather conditions, may be relative to the particular geographic location.

As mentioned earlier, extreme conditions differ in the degree of urgency with which an evacuation may be required, in the degree of predictability, and in the ability to prevent and or control the causing event and its consequences. In Table 1.2, the degree of urgency in evacuation is characterized as high, moderate or low. The urgency increases with the extent to which a given situation may be life-threatening. Control measures are characterized by the extent to which consequences can be contained and confined to a given bounded area, and by the availability of direct actions that may reduce negative impacts. For example, hurricanes cannot be or contained within a given area, and thus the control measures are given a “low” designation. Similarly, while heavy rain cannot be limited or confined within a given area, its effects can be mitigated by a number of measures like better draining and lighting roads for better visibility. However, this dimension for characterizing extreme conditions is admittedly problematic; for example, war may involve a wide range of destructive tools, from nuclear

weapons to conventional grenades, and is considered here as having only moderate control measures.

Although most of the above descriptive factors can change with the severity of each condition, the factors used in Table 1.2 assume the worst case scenario with advanced technological resources. For example, a hurricane may be sufficiently weak that there is no real urgency of evacuation. However, under a worst case scenario, this urgency will be extremely high. On the other hand, with advanced technological resources, the predictability of hurricanes increases. It should be noted that accidents and hazardous physical spills are viewed as having low urgency of evacuation since they normally have limited influence areas.

Finally, extreme conditions can occur both independently and jointly with each other. An extreme condition could be a direct or an indirect consequence of another extreme condition. For example, a traffic accident may cause a chemical hazardous spill if one of the vehicles involved is a trailer carrying dangerous chemical materials. Also, some extreme conditions can occur near-simultaneously, such as floods and heavy rains. An extreme condition may also belong to two different categories, for example a flood caused by destroying a dam intentionally will be considered a terrorist act, whereas a flood caused by heavy rain is a natural disaster. Therefore, boundaries between these conditions should not be viewed as clear cut.

Extreme Condition	Urgency of Evacuation	Control Measures	Predictability
Extreme Heat	Low	Moderate	Moderate
Extreme Cold	Low	Moderate	Moderate
Heavy Rain	Low	Moderate	Moderate
Heavy Snow	Moderate	Moderate	Moderate
Floods	High	Low	Low
Hurricanes	High	Low	High
Tornados	High	Low	Low
Typhoons	High	Low	High
Fires	High	Moderate	Low
Earthquakes	Moderate	Low	Low
Volcano Eruptions	High	Low	Low
Tsunami Waves	High	Low	Low
Meteorites	High	Low	Low
Accidents	Low	High	Low
Hazardous Spills (Physical)	Low	High	Low
Hazardous Spills (Biological)	High	Low	Low
Hazardous Spills (Chemical)	High	Low	Low
Hazardous Spills (Nuclear)	High	Low	Low
Terrorist (Bombing)	High	High	Low
War	High	Moderate	Moderate

Table 1.3: Differences in Extreme Conditions: Urgency of Evacuation, Control Measures, and Predictability

The focus of the present study is on extreme conditions that involve a high degree of threat to human life, and that require evacuation with a high degree of urgency. Accordingly, panic behavior is likely to be an essential element of these situations. The concept of “panic” is presented and discussed in the next section. Finally, extreme conditions could be studied in the context of different transportation modes, such as air, maritime, auto, transit, rail, or bike/pedestrian. The focus of this study is on extreme conditions in the context of the highway and auto-driver mode.

1.3. Panic: Psychological Overview

The literature on panic is characterized by many ambiguities and “tenuous generalizations” (Schmidt and Warner, 2002). The word is often misused in the media and in our everyday language. For example, when reporting about earthquakes (Moore, 1999), train bombings (Jamieson, 2004), or fires (World News, 2004), the news media tend to refer to panic as a simple flight behavior that is the only rational way to respond to such conditions.

Historically, the word “panic” referred to sudden and unreasoning fear in Greek, French, and later English languages (Boulenger and Thomas, 1987). Today, the best description of panic is through the definition of a “panic attack” or “panic disorder” established by the Association of Panic and Anxiety. These definitions are found in DSM-IV (Diagnostic and Statistical Manual of Mental Disorders) with the following criteria (Schmidt and Warner, 2002):

1- DSM-IV criteria for panic attack:

A discrete period of intense fear or discomfort, in which four (or more) of the following symptoms developed abruptly and reached a peak within 10 minutes:

- A- Palpitations, pounding heart, or accelerated heart rate
- B- Sweating
- C- Trembling or shaking
- D- Sensations of shortness of breath or smothering
- E- Feeling of shock
- F- Chest pain or discomfort

- G- Nausea or abdominal distress
- H- Feeling dizzy, unsteady, lightheaded, or faint
- I- Derealization (feelings of unreality) or depersonalization (being detached from oneself)
- J- Fear of losing control or going crazy
- K- Fear of dying
- L- Paresthesias (numbness or tingling sensations)
- M- Chills or hot flushes

2- *DSM-IV criteria for panic disorder:*

- a. Both (1) and (2):
 - 1- recurrent unexpected panic attacks
 - 2- at least one of the attacks has been followed by one month (or more) of the following:
 - i- persistent concern about having additional attacks
 - ii- worry about the implications of the attack or its consequences (e.g., losing control, having a heart attack, “going crazy”)
 - iii- a significant change in behavior related to the attacks
- b. The panic attacks are not due to the direct physiological effects of a substance (e.g., a drug of abuse, a medication) or a general condition (e.g., hyperthyroidism).

- c. The panic attacks are not better accounted for by another mental disorder, such as Social Phobia (e.g., on exposure to a feared social situations), Specific Phobia (e.g., on exposure to a specific phobic situation), Obsessive Compulsive Disorder (e.g., on exposure to dirt in someone with an obsession about contamination), Post-traumatic Stress Disorder (e.g., in response to stimuli associated with severe stressor), or Separation Anxiety Disorder (e.g., in response to being away from home).

The two previous definitions refer to panic as a mental disorder and not as a behavioral state. Historically, the association of panic and anxiety has been “variable and contingent from both a clinical and historical standpoint” (Clark, 1995). Some experts argue that panic and anxiety represent two very different kinds of experience. In the National Comorbidity Survey, modeled on the 1990 U.S. Census, panic ranked as the least frequent anxiety disorder (Schmidt and Warner, 2002). In this study, panic is seen as an extreme case of anxiety; panic attacks are extremely strong anxiety attacks with the same criteria explained in DSM –IV. Accordingly, the criteria are the same in type but different in degree.

Ambiguity and debate still remain about panic being a cognitive state, a physiological state, or a social state. Panic is dependent on and correlated with an individual’s socio-economic environment. “Whatever panic behavior involve, it does represent the behavior of a socialized individual, perceiving and thinking in socially defined and supported ways, reacting to socially interpreted situations, and interacting with and giving meanings to the actions of still other social

beings” (Shultz, 1964). The first studies regarding panic were conducted from a purely cognitive standpoint. However, this kind of approach focuses on the cognitive aspect of panic, overlooking the fundamental roles played by bodily responses and sensations experienced. “The physiological arousals in a panic state both feed into and are fed by the cognitive assessment of a subject, as if body and mind are welded together” (Schmidt and Warner, 2002). More specifically, panic leads to more than a psychological state of mind, but also a physiological response.

Since the behavioral aspects of panic responses are not fully understood, Schmidt and Warner (2002) examined animal behavior under panic situations to clarify this issue. When an animal is faced by danger, it tends to have either an orienting or a defensive behavior. More specifically, the animal tends either to defend itself or to flee the scene. However, this may not solve the problem and the animal will be faced by what is called “perception of inescapability” (Schmidt and Warner, 2002). In this situation, panic feeling will be generated, representing a failure of the organism’s innate defensive structures to mobilize and thus allow the individual to escape threatening situations actively and successfully. However, when orienting and defensive behaviors are carried out smoothly and effectively, panic is not generated. In other words, when the normal orientation and defensive escape resources have failed to resolve a dangerous situation life hangs in the balance with non-directed flight, rage, freezing, or collapse. “Rage and terror-panic are the secondary emotional anxiety states that are evoked when orientation and preparedness to flee are not successful.” (Schmidt and Warner, 2002)

Freezing is also called tonic immobility that is a heightened contraction of agonist and antagonist muscle group. It is the last resort when active escape is not possible. Defining the boundaries of panic from psychological and physiological points of view, panic is now better understood from an individual point of view. However, drivers are defined as an organized group that interacts with each other following some governmental or societal rules (traffic laws). Accordingly, panic should be also seen from a collective point of view.

Among the first studies regarding panic in organized groups, the example taken was military groups. According to Freud, an army is a highly artificial grouping since some external force is required to keep it intact and to maintain its rigid structural integrity (Schultz, 1964). This integrity will help the army serve its purpose. Panic arises when this group disintegrates to the point where: (1) the orders of the superior are no longer attended to, and (2) each individual becomes concerned with his own welfare only and has no consideration for the other members. In other words, panic is considered to result from a “break-down in group structure” (Schultz, 1964).

To help identify more aspects of panic behavior, Quarantelli (1957) analyzed the behavior of people engaged in a panic flight. He based his analysis on tape-recorded interviews with around 1000 persons who were involved in minor or major disasters. The disasters were studied by the Disaster Team of the National Opinion Research Center of the University of Chicago. To help identify the persons subjected to panic, panic was considered here to be only that flight

behavior which is destructive to the group. The following observations were noted:

- 1- Generally, a panicky person is an individual who has been fairly well divested of all or almost all of his socially acquired characteristics. He is thought of as behaving in a completely irresponsible or anti-social manner. The situation is very similar to a wild chaotic stampede.
- 2- The panic participant perceives a specific threat to physical survival. Moreover, he is aware of what he is afraid of.
- 3- The panic participant is future-threat rather than past-danger oriented. His attention is focused on what may occur rather than on what has happened. Accordingly, panicky reactions will occur in situations involving no real threat simply because a threat is possible.
- 4- The panic participant is acutely self-conscious and fearful. The more threatening he perceives the situation to be, the greater his awareness of himself. Moreover, he tends to give an overt expression of his fear if he becomes helpless and powerless to cope with a threat.
- 5- The panic participant is aware of his activities. This may have some degree of conflict with the previous observation. But this suggests that some panic participants still rationalize their decisions to a certain degree.
- 6- The panic participant is non-rational in his flight behavior. There is no involvement of the weighing of alternative courses of action. This is due to the participant's focalization of his thought and consequent overt activity to remove himself from a threatening area.

- 7- The panicky participant is highly self-centered, thinking only of saving himself. In this sense, panic flight represents a very highly individualistic behavior.

The above observations are helpful but still vague in terms of their applicability to and implications for drivers and their behavior. The next section discusses driver behavior in light of the above background on panic.

1.4 Panic: A Driver Behavior Characteristic

Panic behavior can be studied in different contexts. In transportation, panic results from a life threatening situation during extreme conditions. However, as mentioned earlier, not all extreme conditions cause panic because they differ in type and degree. Some extreme conditions, such as extreme heat or cold, may only cause mild anxiety levels; panic is considered the strongest level of anxiety.

At the microscopic level, panic behavior may be distinguished from normative non-panic behavior according to the following dimensions:

- (a) Longitudinal driving: under extreme conditions a driver may accelerate at a high rate and reduce headways to pressure the driver ahead, who correspondingly might do nothing, switch lanes, or attempt to decrease his headway with his predecessor. The shorter headways contribute to increasing the volatility and danger level of the situation. Moreover, a driver may decelerate at a higher rate than needed to avoid collision with

the leading vehicle. This high deceleration rate may be the direct cause of a crash.

(b) Lateral Behavior/Lane-Changing:

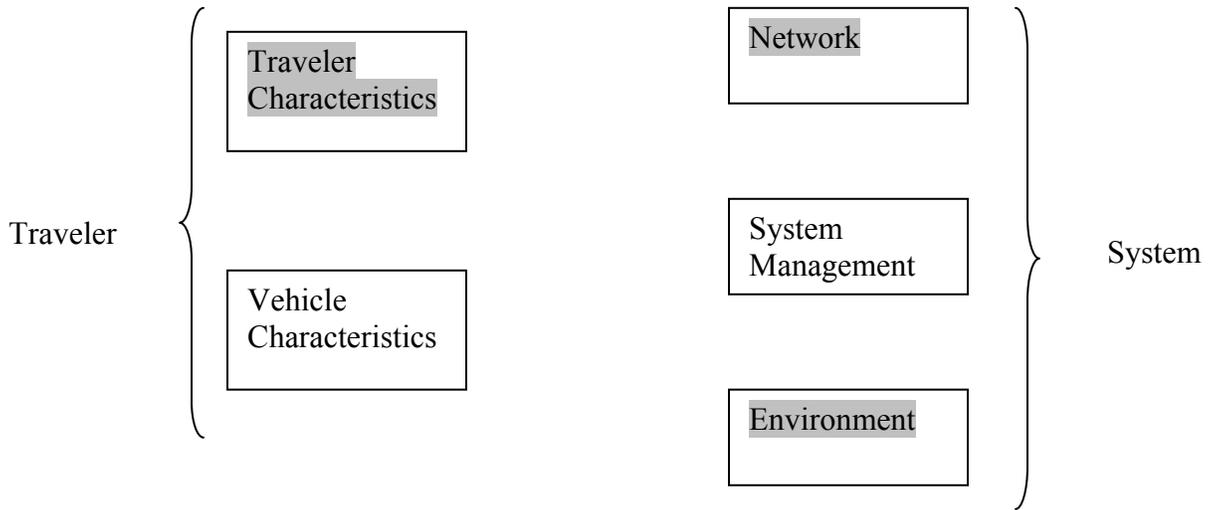
In the case of increased aggressiveness, a driver would be willing to accept small gaps (headways), forcing the car upstream in the receiving lane to break strongly, possibly resulting in a crash. Steering errors and other kinds of control movements are also aspects of panic behavior, though those may be more difficult to describe and model at the microscopic level.

The panic behavior of drivers can be seen as unpredictable and at times totally unmotivated. However, it is not altogether completely irrational behavior. Panic in driving does not mean total chaos. Panicky drivers have a logic that is not too different from that of other drivers. However, they are much more self-centered and may not have the same ability to identify and weigh alternative courses of action. Moreover, when modeling driver behavior under panicky conditions, it should be noted that not all drivers are necessarily in a “panic hysterical” state. It is sufficient for only some of the drivers to engage in “inappropriate” driving to affect the driving of others and cause serious problems in the traffic stream. In some cases, aggressiveness of some drivers will cause an increase of aggressiveness shown by other drivers as a reaction. Accidents will be more frequent and for that, possibly resulting in greater panic. If no control action or intervention is employed in this situation, the drivers could be stuck in a cycle of more aggressiveness that engenders greater panic.

For further characterization of panic behavior, a parallel can be established between the panicky drivers' possible way of thinking and the "animal theory" described in the previous section. Drivers tend to think rationally when first subjected to a life threatening situation under extreme conditions. When they cannot find a solution that deals with the situation, they try to flee in an organized way. However, when it appears that there is little possibility to get rid of the panic source, the "perception of inescapability" sets in. Irrational responses are generated even when other possible coping strategies are still possible. This may cause unorganized fleeing even in the wrong direction. The more time elapses, the more likely are manifestations of non-rational behavior to appear. Drivers can become increasingly aggressive. However, some of the drivers may not even try to flee anymore. Freezing or slowing in velocity could be their response after being unable to cope with the situation.

To study panic in transportation from a collective point of view, drivers could be viewed as an organized group as described by Freud and Shultz previously. The organized group follows some societal rules (traffic laws) established by the "leader": the law enforcement agencies or the government. This structure is necessary to allow the group to serve its purpose: mobility. Once panic situations are encountered, the whole structure starts to break. The authority of the government is seen to be collapsing and respect for traffic laws is progressively eroded. Each driver is now concerned about his/her welfare, possibly increasing the exposure of other individuals to harm.

To understand and define panic behavior, one should understand the nature of traffic networks and the relationship between network infrastructure, environment and drivers using this network. Based on the Next Generation Simulation (NGSIM) Report (FHWA, 2004), the two main components of a transportation network are a) the system that needs to support the traffic and b) the travelers using this system. The aggregate properties of traffic flow, such as Level of Service (LOS) and volume depends on these two components. Figure 1.1 divides these two components (traveler and system) into different subcomponents.



**Figure 1.1: Traveler and System Characteristics
(Selected from NGSIM Task E.1-1, 2004)**

The first component that is not considered in this thesis is the System Management Component since the control measures are typically not in operation during extreme conditions. As for the vehicle characteristics (length, steering capacity ...etc), they are considered identical across all drivers. For that reason, they do not constitute a primary factor to be studied

In each of the traveler and system characteristics mentioned in Figure 1.1, there are some major aspects that would affect driver behavior. These aspects are listed in Table 1.4 (FHWA, 2004).

<i>Major Factor</i>	<i>Aspects affecting Traveler Behavior</i>
Traveler Characteristics	Decision Making: 1-Familiarity of drivers with network 2-Driver aggressiveness 3-Driver value of time
	Compliance: 1-Speed limits 2-Traffic Signals 3- Ramp Metering 4-Lane Restrictions/usage 5-Road type preference
Network	Link Geometry: 1-Facility Type 2-Grade&grade changes 3-Auxiliary lanes 4-Route restrictions/land use 5-Sight restrictions
	Intersection Geometry: 1-Angle between links 2-Flared angles
Environment	Incidents: 1-System Effects (lane closures) 2-Behavioral Effects (emergency braking, rubber-necking)
	Work Zones: 1-System Effects (variable/reduced speeds) 2-Behavioral Effects (emergency braking, rubber-necking)
	Weather: 1-System Effects (localized reduced visibility, systemwide reduced surface quality)

**Table 1.4: Influence Factors on Traveler's Behavior
(Selected from NGSIM Task E.1-1, 2004)**

Under extreme conditions, the compliance of drivers with traffic laws and information from management systems may be reduced. Drivers would be expected to ignore traffic laws instead of complying with them.

Finally, there is no single source describing driver panic behavior under extreme conditions. The characteristics of panic behavior are obtained from three types of resources. The first type is based on personal suggestion combined with media fliers related to aggressive driving. These fliers can be found in newspapers or in campaigns for safe driving (National Highway Traffic Safety Administration, U.S. Dept. of Transportation, 1998). The following characteristics come from this source:

- 1- Tailgating (decrease of headways) to pressure a driver to go faster or get out of the way.
- 2- Using the vehicle to retaliate by making sudden, threatening maneuvers.
- 3- Sudden lane changing.
- 4- Increase in the number of accidents leading to an increase of congestion.
- 5- Emergency breaking and rubber-necking.

The second type of characteristics is deduced from psychological and social definitions of panic behavior presented in Section 1.2. For example, the disrespect of traffic signals and signs is based on Freud's definition of panic behavior: the structure of the transportation system is seen to collapse without respecting the rules that holds it together. These characteristics are listed below:

- 6- Increase in velocity for aggressive drivers, resulting in higher acceleration and deceleration rates.
- 7- Decrease of critical allowable gaps.
- 8- Tendency to disrespect traffic signs and signals.

9- Increase in intensity of panicky reactions (velocity, breaking rates, aggression ...etc) with time as long as the source of panic is still present.

Finally, characteristics were taken from various papers studying related subjects. The following characteristics are based on the features of escape panic for pedestrians (Helbing, 2000):

10- Herding Behavior: many drivers are not normally aware of the possible network exits that allow them to escape from a given dangerous situation. In that case, they tend to follow the main stream of traffic hoping that it will lead them to these exits, generating a traffic pattern called mass or herding behavior. This mass behavior may cause congestion and bottlenecks during extreme conditions.

11- Clogging at critical zones leading to longer queues.

The final characteristic is based both on psychological analysis of panic behavior and on the differential of velocities suggested by Daganzo (1999):

12- Higher variance in velocities due to drivers freezing or slowing down for not being able to cope with a specific threat.

There should be no confusion between a panic behavior and a result of a panic behavior. The 12 characteristics mentioned above are all panic behaviors except Characteristic 4 and Characteristic 11; an accident is not a behavior in itself but a consequence of the aggressiveness, lack of alertness, or disrespect of traffic laws shown by some drivers. On the other hand, clogging is an aggregate result of individual driving patterns in a given traffic situation.

1.5. Problem Statement

This thesis examines the effect of extreme conditions on drivers' behavior and thus the affect on vehicle trajectories and aggregate traffic flow properties in a simplified transportation network. In analyzing extreme conditions, the definition and conditions of "panic behavior" requires attention. However, the ambiguities associated with the word "panic" have led to the absence of a consensus on a clear definition of this type of behavior. For that reason, no existing traffic simulation model adequately addresses driver behavior under extreme conditions. Thus, this thesis ultimately aims at defining individual panic behavior as it relates to extreme conditions and under this definition, examine driver behavior under extreme conditions.

Based on the above problem statement, the main objective of this study is to model individual panic behavior of drivers under extreme conditions. More specifically this thesis aims to:

1. Formulate a micro-simulation model capable of capturing and accounting for driver behavior under extreme conditions.
2. Validate this model against real-life vehicle trajectory data.
3. Conduct a sensitivity analysis to determine the range of applicability of the suggested model.

In the previous two sections, the scope of panic behavior and extreme conditions was presented, analyzed, and defined. Accordingly, modeling driver behavior under extreme condition requires further effort and research. Extreme conditions give rise to different types of behaviors. The focus of the present study is

concerned with extreme conditions associated with panic behavior or high urgency for evacuation (Table 1.1).

Modeling the panic behavior of drivers is difficult. Section 1.2 helped define the scope of panic behavior and reduced it to specific behavioral attributes. The micro-simulation model aims to capture the largest possible number of the behavioral attributes mentioned in Section 1.4.

Chapter 2 aims to review different existing driver behavior models and their strengths and weaknesses. Each model is assessed and evaluated with respect to its suitability to model panic behavior. Accordingly, this will help in formulating and implementing a model of driver behavior in this thesis. This model will be presented and discussed in Chapter 3.

Additionally, since no data are available under extreme conditions, calibrating the model in this thesis is near impossible. Thus, this study is restricted to using numerical examples and a sensitivity analysis to illustrate different effects of panic behavior on driver behavior. This sensitivity analysis is presented in Chapter 4. Finally, Chapter 5 presents some concluding remarks.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

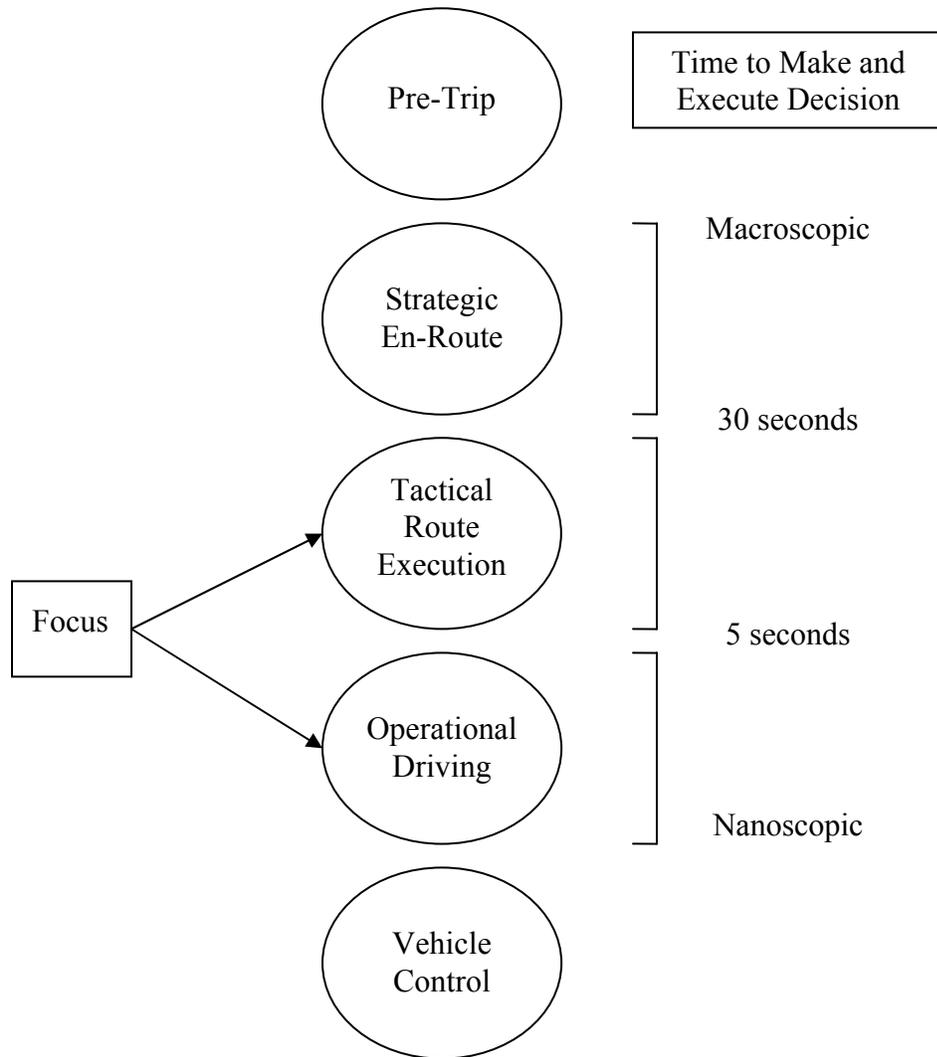
The models presented and discussed in this chapter capture drive behavior at the individual level decisions, collectively giving rise to aggregate traffic flows. Although this thesis aims to provide a model of driver behavior that can describe and capture panic behavior, as defined in Chapter One, this chapter will present and discuss existing micro and macro simulation traffic flow and driver behavior models that have applications beyond panic. An assessment and evaluation of these models will help identify shortcomings of existing models.

Travel decisions occur at five different time horizons or levels:

- 1- Pre-trip: consists of the decisions made before starting a trip (departure time choice, mode choice).
- 2- Strategic en-route: involves the decisions that travelers make en-route, while executing a trip. These decisions usually impact the overall structure of the trip (route choice and switching).
- 3- Tactical en-route: a consequence of small multi-part decisions that are made to complete a small but coordinated portion of a trip (lane-changing, overtaking).
- 4- Operational driving: this is the main focus of this study. Operational driving behaviors represent decisions that a traveler make “on a near instantaneous basis,” typically to satisfy an immediate goal” (acceleration, gap acceptance).

5- Vehicle control: vehicle control decisions are made instantaneously and satisfy human-machine interaction needs.

These five levels are shown below in Figure 2.1 in relation to the approximate time needed to execute decisions at each level.



**Figure 2.1: Classification of Traveler Behavioral Models
(Selected from NGSIM Task E.1-1, 2004)**

Figure 2.1 above illustrates the time scales at which different behavioral models adopted in this chapter occur. Several models have been developed by various

researchers within each level. The table below lists the behavioral models that will be assessed:

Behavioral Model Category	Existing Research	
	Major	Moderate
Operational	Acceleration	Gap Acceptance
Tactical	Lane Changing	-

Table 2.1: Driver Behavior Models Reviewed

Note that models dealing with parking, transit, pedestrians are not mentioned here since they are not the object of interest in this study. The main issue to be analyzed is vehicular traffic on freeways.

2.2. Operational Models

Operational driving decisions are defined in this thesis as the decisions that drivers make on a near instantaneous basis so as to satisfy an immediate goal of a given trip. Based on Figure 2.1, these decisions take less than five seconds to execute. Acceleration (car-following) models and gap acceptance models are discussed next.

2.2.1. Acceleration (Car Following) Models

Acceleration models are at the core of operational behaviors. These models are still referred to as car-following models since early research focused exclusively on interactions between a lead and following vehicle. Fundamentally, car-following models aim at describing the trajectory of the n^{th} vehicle in a traffic

lane given the trajectory of the $(n-1)^{\text{th}}$ vehicle in the same lane. Accordingly, the main assumption in these models is that a correlation exists between vehicles traveling on the same lane when inter-vehicle spacing is within a range, typically between 0 to 125 meters (Rothery, 1999). According to Boer (1999) modern acceleration models are structured to account for several factors such as i) task scheduling and attention management; ii) the use of perception rather than Newtonian variables; and iii) satisfy a performance evaluation strategy, rather than an optimal one.

Researches have employed many different approaches, such as physical, psycho-physical, fuzzy-logic, and agent-based cellular automata (give references for each of these approaches), towards building car-following models. Among the first proponents of the car-following concept was Pipes (1953). He developed “theoretical control-system expressions” for the accelerations applied by the follower given the leader’s behavior. Pipes assumes that the follower vehicle wishes to maintain a safe headway equal 1.02 seconds. However, this assumption is unrealistic under extreme conditions that lead to panic behavior. First under extreme conditions, drivers may not consider safety issues, and thus exhibit riskier behavior compared to normal conditions. Second, even if safe headways used, they most likely vary among locations, drivers, and traffic conditions. According to the Next Generation Simulation (NGSIM) Report (FHWA, 2004), acceleration models can be classified into the following categories: i) stimulus-response models; ii) desired measures models; iii) psycho-physical models; iv) multi-regime models; v) intelligent driver models; and vi) cellular-automata.

Stimulus-Response Models

Herman et al. (1959) and Chandler developed several car-following models at the General Motors Research Laboratories. These researchers were the first to introduce the sensitivity-stimulus framework, under which driver acceleration behavior is a reaction to environmental stimuli. According to this framework, the response (acceleration/deceleration) is lagged to account for perception and reaction time (sensitivity). The GM models (also called Gazis-Herman-Rothery or GHR models) assume that stimulus is determined by the relative speed of the following vehicle with respect to the leader. However, this approach ignores important latent stimuli, such as visibility and weather, which are important especially in the context of extreme conditions. Moreover, this assumption does not account for uncongested free-flow conditions.

Five generations of car-following models were developed by GM (May, 1990). The simplest model is the linear car-following model (Chandler, et al., 1958; Herman, et al., 1959). Gazis et al. (1959 and 1961) extended this model to overcome basic limitations. First, the steady-state equations derived from the linear car-following model were integrated to obtain a linear-flow-density relationship, accordingly identifying two car-following behaviors, one for congested and one for uncongested conditions (Ceder, 1976). Additionally, efforts have also been made to identify new parameter values that provide better fit to the available data (Brackstone and McDonald, 1999; Aron, 1988; Ozaki, 1993). After examining a number of macroscopic and microscopic models, May and Keller (1967) show that all the previously discussed models can be reduced to a general

car-following equation by selecting appropriate shape parameter values (m and l) from a range of values. However these parameters do not have intuitive or behavioral interpretations related to traffic flow. Additionally, they need to be calibrated each time to fit given traffic data.

Desired Measures Models

Desired measure models assume that the driver maintains a desired speed or headway measure, so as to minimize both the relative speed to the leader and the difference between the actual space headway and the desired one. These models address a deficiency of the GM model by allowing the spacing between two successive vehicles traveling at the same speed to take any value. One improvement over these desired measure models is the development of a four-component model that attempts to explain acceleration behavior in standard car-following, by incorporating the effects of gradient, acceleration from a standing queue, and acceleration in free-flow regimes (Xing, 1995).

In an optimal velocity model the optimal speed is a function of the space headway with respect to the leader (Newell, 1961; Bando, et al., 1995). The acceleration the driver applies is proportional to the deviation of the actual speed from the desired one. However, in panic and extreme conditions aggressive drivers may not accelerate or decelerate proportional to headways.

Psycho-Physical Models

Psycho-Physical models extend the GM models by addressing two assumptions. First, these models relax the assumption that the drivers follow their leader even when the distance between them is large. Second, the perception and reaction are not sensitive to small changes in stimulus (Michaels, 1963; Todisiev, 1963). To address these two assumptions, the concept of perceptual thresholds is introduced to define a perceptual threshold that defines a stimulus range within which the driver of the following vehicle would not notice any change in his conditions and thus would maintain a constant acceleration. This plays an important role in modeling and describing panic behavior especially since the sensitivity (perceptual thresholds) of the drivers may decrease during extreme life-threatening conditions.

The perceptual threshold is low for short headways and increases infinitely for large headways, representing an increase in driver alertness for small headways and the lack of explicit car-following behavior for large headways (May 1990). However, during panic situation car-following behavior may not strongly govern acceleration behavior even for small headways, since drivers tend to function as independent individuals and not as a collective group. Additionally, perceptual thresholds are different for acceleration and deceleration decisions.

Multi-Regime Models

As mentioned earlier, car-following models aim at capturing and describing more general acceleration and deceleration behaviors of drivers. Multi-regime models aim at capturing a wide range of acceleration/deceleration behaviors. Gipps (1981) developed the first car-following model that applies to both congested and free-flow conditions. He suggests that a maximum acceleration is determined based on two main constraints: i) the driver's desired speed that may not be exceeded; ii) a minimum safe headway that the driver must keep. The safe headway is based on the minimum headway that allows a driver to avoid collision with its leader if the leader applies emergency braking. However, this assumption leads to a crash-free model that cannot be applied for extreme conditions. In a similar model developed by Benekohal and Treiterer (1988), the assumption of a safe headway is relaxed since headways can be reduced to shorter than safety limits due to driver aggressiveness or look-ahead behavior. Nonetheless, Gipps-type models, in their deterministic limit, are ill suited to capture traffic instabilities or hysteresis effects, which exist in the real world (Treiber, et al., 2002).

Another general acceleration model developed by Yang and Koutsopoulos (1996) assumes drivers change their behavioral patterns based on one of three regimes they follow: i) emergency; ii) car-following; iii) free-flowing. The emergency regime allows the driver to apply necessary deceleration to avoid collision with its leader. As mentioned earlier, this assumption does not

necessarily hold for panic behavior. A similar multi-regime acceleration model is based on the space headway instead of the time headway (Zhang, et al., 1998).

Intelligent Driver Model (IDM)

A vehicle's acceleration in the Intelligent Driver Model (IDM) is a continuous function of the vehicle's current velocity, the ratio of the current spacing to the desired spacing, and the difference between the lead and the following vehicles' velocities (Helbing, et al., 2002; Treiber, et al., 2002). In this model, the desired gap size is not a factor calibrated by the modeler. It is given by a dynamic equation which varies with the driver's velocity and the rate of approach giving the driver more "intelligence." Their ability to capture time-varying characteristics allows IDM models to be more realistic.

Cellular Automata (CA)

Cellular automata (CA) models use discrete space systems to represent all types of behaviors. However, the focus of most of the existing models is on car-following behaviors, because of their role in traffic stability phases. However, rather than being considered a new and different behavioral model, CA systems are implemented as discretized versions of older car-following models. They provide a computationally efficient method for simulation of large scale networks since they are discrete dynamical systems: space, time, and properties of automaton have finite, countable number of states. The objective of CA is to not describe and model complex system with complex equations, but let the

complexity emerge by interaction of simple individuals following simple rules (Schatten, 1999). This is similar to an agent-based simulation framework where the complex behavior of the system emerges from the behaviors and interactions of individual agents. Two main properties of CA models are: i) a regular n-dimensional lattice (n is in most cases of one or two dimensions), where each cell of this lattice has a discrete state; ii) dynamical behaviors described by so called rules. These rules describe the state of a cell for the next time step, depending on the states of the cells in the neighborhood of the cell.

Cremer and Ludwig (1986) and Nagel and Schreckenberg (1992) were among the first researchers to develop CA models. The application of these models to traffic dynamics attracted many others, especially physicists. The aim is mainly to understand traffic instabilities that are the central cause for congestion (Helbing, 2001). However, CA models offers only crude estimates of the real dynamical behavior of an individual vehicle. Additionally interactions among drivers are difficult to relate to interaction between cells in CA models.

Synthesis of Car-Following Models

Gaziz-Herman-Rothery or GHR models were the first implemented models. However, the lack of conclusive evidence to the behavioral linkage of the GHR equation to the real driving behavior has led to its decline. Moreover, there is a lack of an obvious relationship between the GHR variables and the identifiable characteristics of drivers or vehicles (Gipps, 1981).

Desired stimulus models are easy to calibrate. This may be due to the estimated parameters which do not account for other influences such as lane geometry, weather conditions, or risk-taking behavior of the drivers.

Psycho-physical models capture the interaction between driver-vehicle units with other driver-vehicles units based on the drivers' perceptions of the relative motions of the other vehicle's movements to its own. These models have multiple parameters and can be difficult to calibrate.

Multi-regime acceleration models could fall into any of the previous three types with different equations applied to different regimes. Although they show realistic behavior, they rarely show traffic instabilities. The model by Zhang and Kim (2000) is the one of the few existing models claiming capability of modeling capacity drop and traffic hysteresis.

IDM models are new and promising especially since the dynamic equations associated with the velocity characterizes realistic driver behavior. CA models require extensive calibration to be operational.

Car-following models are both a type of model for driver behavior and a foundation for implementing predictive microscopic model. These models are the easiest to validate. The amount of variation in acceleration model validation is small (Wagner, et al., 2002) and few parameters require estimation. This is due to presence of rigid assumptions about the homogeneity of decisions made by each driver class. On the other hand, the main shortcomings in acceleration models concern the exclusion of direct environmental and system management effects. Weather is an influence on car-following models that has not been fully studied to

date. Finally, the applicability of car-following models to mixed traffic situations is an issue for future research.

2.2.2. Gap Acceptance Models

The concept of gap acceptance is mainly important for unsignalized and signalized behavioral models. “In general, there are two types of gap acceptance: i) crossing gap acceptance at intersections; and ii) gap acceptance during merging or lane changing maneuvers. The main interest for this thesis is the latter type. Two gaps (lead and lag) are considered by the prospective leading and following vehicles, respectively and all three vehicles (the leading, lagging, and vehicle of interest) are moving at speed. It was assumed originally that both merging and crossing maneuvers behave in the same way (Raff and Hart, 1950; Haight, 1963). Later on, researchers suggest that merging gap acceptance should be treated differently (Drew, et al. 1967). This section will focus on crossing gap acceptance models for vehicles at signalized and unsignalized intersections, with the main focus on critical gaps. Unlike in the Highway Capacity Manual (HCM, 2000), in micro-simulation models the critical gap is used to describe the threshold used by a particular driver to determine acceptability of a gap, which is better in terms of modeling gap acceptance under panic behavior. The empirical studies done by HCM were not based on data collected during extreme conditions. Moreover, the assumption that the critical gap is equal to the median of the distribution of gaps accepted by all drivers implausible since most likely it varies across drivers.

Deterministic/Distribution Gap Acceptance

Most of the gap acceptance models are formulated as a binary choice. Drivers either accept or reject a presented gap in the current time interval, relying on the comparison of the existing gap with the driver's critical gap. The driver's decision is assumed to be based upon perfect perception and information on the approach vehicles' attributes, such as acceleration. Under extreme conditions, this assumption does not hold. Moreover, in deterministic approaches, a driver's critical gap is assumed to be constant. In distribution gap acceptance, although critical gaps vary with drivers, it does not vary across time. However, gap acceptance is a situational decision that depends on a driver's present conditions (Daganzo 1981).

The random component in deterministic/distribution critical gap acceptance models has been formulated using critical gaps as random variables with various distribution forms." Early research assumes that the value of the critical gap is between the value of accepted and rejected gaps (Raff and Hart, 1950). Under the same concept, an exponential distribution of critical gaps between the two values was first assumed by Herman and Weiss (1961). Drew, et al. (1967) assumed a lognormal distribution. After conducting a review on nine critical gap estimation methodologies from the 1960s to the 1970s, Miller (1972) concluded that the maximum likelihood estimator gives the best estimation of the value of the critical gap. After different updates and improvements over the years, Troutbeck (1992) presented a more precise form.

The main framework to form gap acceptance methodologies to calculate capacity is founded on the research conducted by Siegloch (1973). This framework is only valid for saturated conditions and impractical for many other situations, such as uncongested situations and panic conditions. Briton, et al. (1999) later reviewed several gap acceptance methodologies and recommended the maximum likelihood estimator for the critical gap (Troutbeck, 1992) as the most appropriate for capacity estimation.

The first maximum likelihood method started in 1968 (Miller and Pretty, 1968) and it assumes that each driver d has two values: 1) r_d or the largest rejected gap (in seconds), and 2) a_d , or the accepted gap (seconds). The model determines the probability of critical gap t_c , bounded by r_d and a_d . Typically t_c is assumed lognormally distributed. However, the main issue in modeling gap acceptance is the priority/right-of-way rules that are typically inapplicable to extreme conditions. Moreover, some influencing factors, such as ..., are not included in most of these studies and the parameters do not represent vehicle-driver characteristics related to panic behavior. These models are based on probabilistic-economics theories more than they are based on direct traffic relationships. This same problem is to be discussed in the next sub-section.

Deterministic/Distribution Gap Acceptance Parameters

Most of the parameters of concern in the context of gap acceptance, such as type of maneuver, speeds, geometric characteristics, and sight distances, are presented for qualitative discussions, alternative model formulations, or

determining critical gap default values rather than a microscopic description of how individual driver decisions are made].

One variation of standard gap acceptance maneuvers is the two-stage gap acceptance maneuver performed at intersections with medians and two-way left-turn lanes (TWLTLs). The near-side traffic is crossed first. Next the driver stops in the median area, while searching for a gap on the far-side of traffic. The HCM simplifies this maneuver by dividing it into two parts: the first part is the vehicle maneuver from the original travel lane into the TWLTL, and the second maneuver is performed between the TWLTL and the minor street.

A second variation of gap acceptance is with U-turn maneuvers. This can be treated with the assumption that vehicles need to consider two different gaps: i) the crossing gap; ii) the gap required to execute the U-turn without excessively impeding the progress of oncoming vehicles. However, limited attention has been given to this concept of gap-acceptance with U-turns and no parameters specific to U-turns has been included.

The final parameter discussed is the driver/vehicle waiting time. A given driver's critical gap typically decreases over time as his patience becomes more limited. The decrease is strongly correlated to the time spent waiting at the intersection (Mahmassani and Sheffi, 1981). During extreme conditions, drivers may see the urgency of evacuating as a reason to accept shorter gaps and their impatience grows much stronger, but past studies have not addressed this issue.

Probabilistic Gap Acceptance

The main shortcoming of deterministic/distribution gap acceptance methodologies is that they cover variation in critical gap values across drivers and situations, but given the same factors (major stream traffic volumes, maneuver type, waiting time) the same driver will choose the same gap. Probabilistic gap acceptance models are formulated to capture random variability in gap acceptance across individuals; there is some random error in the choices people make and that needs to be captured

In 1981, driver-specific variation in critical gap was first introduced using a multinomial probit formulation of critical gaps (Daganzo, 1981). In this study the mean critical gap t_c is a function of influencing factor variables and is modified by a random variable ε that is distributed Normal with a zero mean.. Each gap observed by a driver has a probability of either being accepted or rejected depending on the gap's length. Accordingly, this formulation requires a specific set of coefficients for each driver class or driver characteristic dimension to be estimated.

Mahmassani and Sheffi (1981) allowed the mean of the distribution of critical gaps to be a function of influencing factors of a given function. Their main focus was on the driver's wait time at intersection. The critical gaps were assumed to be normally distributed. The authors concluded that the number of rejected gaps by a given driver had a significant influence on the gap acceptance behavior of individuals. Accordingly, the value of time proved to be an important factor and in the case of panic behavior for gap acceptance, it should be equally as

important. Also at stop-controlled intersections, total queuing time was used instead of waiting time as to reflect the impatience factor in the reduction of the critical gap value (Madanat, et al., 1994).

In addition to probit models, logit models were also used to formulate probabilistic gap acceptance. Cassidy, et al. (1995) applied a logit model for stop-controlled T-intersections. In this study, initial lags are differentiated from subsequent gaps and gaps in the near lane are differentiated from gaps in the far lanes. This differentiation was done by introducing dummy variables to the logit model.

Simple gap acceptance models for low volumes have a tendency to overestimate the capacity of flow in the direction with the right-of-way and to underestimate for high volumes. Probabilistic approaches aim to decrease this type of error. The main tradeoff in gap acceptance models concerns the gap acceptance parameters included to capture differences in gap acceptance across the driver population. Models with single, globally applicable parameters are easiest to estimate, but not likely to be appropriate for all conditions (extreme conditions, geometric conditions and others). Models with many parameters are more difficult to calibrate and estimate.

Even with huge amounts of data, there is limited evidence that supports gap acceptance procedures. A critical gap that applies to all situations across all individuals is intuitively implausible. Moreover probabilistic gap acceptance models do not significantly affect the capacity and performance of the simulation packages. Another problem is the quality of parameters used and not their

quantity. The question of how to include the influences factors explicitly rather than as a “proxy-effect” that must be configured by the user is still to be answered. For example, visibility is an important factor in weather extreme conditions, but is not directly presented in most gap acceptance models. Other issues are related to the unrealistic exact prediction of drivers to the speed, location, and gap size of each and every oncoming vehicle. Moreover, in micro-simulation models, such as CORSIM and VISSIM, when a vehicle crosses in front of a driver, this driver tends not to react at all; this situation rarely occurs in real traffic conditions even at tight bumper-to-bumper tolerances. Finally, the assumption that all accepted gaps are safe gaps is the main limitation in these models. Under extreme conditions, drivers tend to force their gap. Drivers typically create an acceptable gap for themselves by assuming that the right-of-way will react to avoid a collision. This will create many accidents that can not be captured by existing gap acceptance models.

2.3. Tactical Models

Tactical behaviors are performed to achieve short term objectives in a given trip from origin A to destination B. They represent small, multi-part decisions to complete a small, but coordinated, portion of a driver’s trip plan.

2.3.1. Lane Changing Models

Lane-changing can be considered an operational and a tactical behavior depending on its interpretation. Lane changing is simple physical act of changing

lanes during driving and can be considered an operational level decision. However, the logic behind the selection of the destination lanes is a much complicated task that should be studied at the tactical level. In the model discussed in Chapter 3, lane changing will be operational in nature especially since the boundary conditions of this model do not take into consideration more than two lanes or a complicated transportation network.

Although it has not been as extensively studied as car-following models, interests in lane changing models have grown since the complexity of micro-simulation models have also grown and the computational ability of present computers has increased. The first lane changing logic is seen in TEXAS (Rioux, 1977; Lee, 1977) and in an earlier work by Fett (1974). It consisted of a simple decision to consider a lane-change or not; a choice of lane; a search of an acceptable gap to execute the lane change; and the selection of the trajectory for changing lanes. According to Gipps (1986), before executing a lane change, three major questions should be asked:

- Is it possible to change lanes?
- Is it necessary to change lanes?
- Is it desirable to change lanes?

Gipps Model

Based on the work of Wiedman and Hoopshneider (1977), a clear illustration of the lane changing decision process was adopted in the Gipps Model (1986). The Gipps model covers different situations under which the lane

changing maneuvers are performed. Traffic signals, transit lanes, obstruction and presence of heavy vehicles are all taken into consideration. As mentioned above, the effects of three major factors are studied: i) necessity; ii) desirability; iii) safety in accepting tolerable lead and lag gaps. Moreover, the study assumed the motivation behind changing lanes is governed by: i) maintaining a desired speed; ii) being in the correct lane for an intended downstream turning maneuver.

Under extreme conditions, the safety is not considered a main issue anymore. Drivers are willing to take greater risks since their main priority is to evacuate a given area regardless of the safety of the other drivers and their own. Drivers tend to realize and weigh future dangers, such as dying in an earthquake, more heavily than the present ones, crashing into another vehicle. This is one of the panic behavioral characteristic discussed in Chapter 1. Moreover, being in the correct lane for a downstream turning maneuver is not considered if driver behavior is to be modeled on a straight free-way with no exits (Chapter 3). However, in other conditions, the relative importance of considerations i and ii changes with the remaining distance to the intended turn. The Gipps model divides every link into three decision zones. In the first zone, the driver is far away and the turning direction has no effect on the behavior of the driver. The main stress will be on maintaining a given desired speed. In the second (middle) zone, the only lanes considered are the turning lanes or the lanes adjacent to the desired turning lane. If the driver is located in the third zone, he is very close to turning. Accordingly, the desired speed is almost ignored and the focus is on keeping the car in the correct lane to make the turn. Under extreme conditions, the

main focus may be on maintaining a desired speed, which will take precedence over being on the correct turning lanes. This further suggests that the length of the third zone should be decreased in favor of the first and the second zone lengths under extreme conditions.

The lengths of decision zones were first defined deterministically based on the physical link length. Variations across drivers were not considered. When more than one lane is acceptable based on the above conditions, the conflict is resolved by considering the following (in order of importance): i) locations of obstructions; ii) presence of heavy vehicles; iii) potential speed gain.

Although the Gipps model accounts for many different situations, no known validation effort of the model's parameters with field data has been conducted. The difficulty lies in the nature of these "abstract" parameters that do not represent or capture any considerable physical meaning and thus making the validation process harder.

Mandatory and Discretionary Lane Change Models

CORSIM classifies lane-changes as either mandatory (MLC) or discretionary (DLC) (Halati, et al., 1997; FHWA, 2002). MLC is performed if the driver is leaving the current lane to exit to an off-ramp. DLC is seen when no requirement to meet such a downstream turning movement or to avoid a blockage is posed. The driver perceives that the lead vehicle is traveling at a speed below some percentage of the link's free flow speed. A potential risk factor is computed for each potential lane-change. It is measured by the deceleration a driver will

have to apply if the leading vehicle brakes to a stop. The calculation of this risk factor applies to the subject vehicle with respect to the intended leader and to the intended follower with respect to the subject vehicle. The risk factor is compared to an acceptable risk factor, which depends on the type of lane-change to be performed and its urgency. During extreme conditions, the perceived degree of urgency in changing lanes is high and accordingly, the acceptable risk factor can be set higher than normal. One of the weak points found in CORSIM is the inability to model lane changing explicitly. Vehicles are only considered to be in one lane or another. However, it should be noted that in panic behavior, there is an abrupt lane changing decreasing the time needed to execute this maneuver. The variability across drivers is another issue. In DLC, this is dealt with using an aggressiveness factor represented by the intolerable speed under which a driver is willing to change lanes. DLC is also determined by a user-specific minimum potential headway and maximum potential headway in the target lanes. Driver types are motivated for DLC according to the headway value. Under extreme conditions, one of the possible modifications to this type of model is to change the velocity thresholds and the minimum and the maximum headways mentioned above. For example, aggressive panicky drivers tend to have higher velocities below which they intend to change lanes. Also, the minimum headway is lower since they have no problem in tailgating the leading vehicle. Moreover, they accept shorter gaps in the adjacent lane to perform their lane changing maneuver.

In MLC, aggressive driving is related to an urgency factor. In this urgency factor, the following issues should be taken into consideration:

- The number of lanes required to reach the turning movement
- The link free-flow speed
- The driver aggressiveness factor
- The distance to the downstream object that is causing the MLC

The urgency threshold is specified, such that for urgency values up to the threshold, the vehicle will accept only normal deceleration to execute a lane change. For urgency values above this threshold, the acceptable deceleration rate is increased linearly to the maximum acceptable deceleration. The emergency braking encountered under panic conditions could be imitated by decreasing these urgency thresholds, making higher deceleration rates are then more frequent. In ARTEMIS simulation package, a cooperative lane change is added (Hidas and Behbahanizadeh, 1999; Hidas, 2002). Under heavily congested traffic conditions a vehicle in an MLC situation may change lanes through cooperation with an intended follower. Cooperative behavior models are based on the logic that the follower will be willing to allow this lane changing based on his aggressiveness. However, they are not discussed in this thesis since little research is performed in that domain. Moreover, this kind of behavior is not representative of panic situations. Drivers are more individualistic and “selfish” with little or no cooperation expected. As with most other operational implementations, ARTEMIS does not model the exact lane changing maneuver explicitly. It represents it as an instantaneous movement after delay time representing the lateral motion from one lane to the other. As mentioned earlier, this delay is shorter under extreme conditions.

A MLC/DLC distinction is introduced in INTEGRATION (Van Aerde, et al., 1996). Potential speeds in either adjacent lane are computed in the case of DLC. They are then compared to pre-specified bias distribution to stay in the current lane or to change lanes either to the left or to the right. As in CORSIM, the main constraint added is the inability to have a subsequent lane change for a specified time after the last change. This can be relaxed by:

- Ensuring that the lane change occurs over a finite time period
- Ensuring some lapse time between the end of one lane change and the start of another.

During lane changing, both the lanes are considered occupied so the headway in the starting lane does not appear longer causing the next vehicle following in that lane to speed unrealistically. This same condition is added to TEXAS simulation package with the vehicle being on “both lanes during the lane change for the first approximately 60 percent of the change (Rioux, 1977; Lee, 1977). For that, the lateral position of the change maneuver is represented explicitly using a cosine curve from the initial trajectory in the starting lane to the final trajectory on the subsequent lane. It can be argued that in panic behavior, the vehicles will consider increasing their velocity even if knowing that a preceding vehicle is changing lanes. Accordingly, a vehicle occupying both lanes could be a safe modeling technique.

MITSIM also uses a MLC/DLC model (Yang and Koutsopoulos, 1996). MLC will be called by vehicles to connect to the next link on their path, bypass a downstream lane blockage, avoid entering a restricted-use lane, and respond to

lane use signs and variable message signs. The response to these signs is not a major issue under extreme conditions. The main difference with previous MLC/DLC models is that the conflicting goals are resolved probabilistically based on the utility theory models. The parameters related to the utility models are not explicit and can not be interpreted intuitively. When the speed of the leading vehicle is below the desired speed, a DLC is considered.

On the other hand, the MLC/DLC considered in HUTSIM is related to a traffic pressure function (Kosonen, 1999). The DLC is related to the desired speed of a vehicle to the speed of the leader vehicles in the current and target lanes. If the pressure is lower than a sensitivity threshold in either of the adjacent lanes, then the lane changing decision is activated. However, even if the sensitivity threshold can be modified under extreme conditions, the main drawback of this approach is not taking into consideration the follower vehicle and its influence on the lane changing decision.

In FLOWSIM, fuzzy relationships are introduced among the variables in an attempt to incorporate the uncertainty and imprecision of human decision-making (McDonald, et al., 1997). Even if these models can provide more realistic type of behaviors, they can not explicitly be modified to imitate the twelve behavioral characteristics of panic discussed in chapter 1.

Integrated MLC/DLC

The initial MITSIM model was improved by creating a general lane-changing model that captures both MLC and DLC situations (Ahmed, et al., 1996; Ahmed, 1999). Three steps are introduced to imitate the lane-changing process:

- A decision to consider a lane-change
- Choice of a target lane
- Acceptance of gaps in the target lane

A discrete choice framework is used to model these decisions; “when a MLC does not apply or the driver chooses not to respond on it, a decision whether to choose a DLC is made”. A Logit is used to model this decision process in two steps. First, a driver sees if he is satisfied with the driving conditions in his current lane. This based on his velocity of the preceding vehicle, the presence of a heavy vehicle in front of him and the tailgating effect from the following vehicle. If the driver is not satisfied with these driving conditions, he will start to compare the utility of the current lane with that of the neighboring lanes. This latter utility depends on the speeds of the lead and the lag vehicles in these lanes and the current and desired speed of the subject vehicle.

Adaptive Acceleration MLC/DLC

In all the lane changing models discussed before, the driver tends to maintain a given speed while accepting a particular gap. However, in many observations, drivers tend to change their acceleration so their speed will be acceptable while choosing a target gap. This kind of behavior is called adaptive

acceleration behavior (Zhang, et al., 1998; Toledo, 2003). The interesting point about these MLC/DLC models is that they include an additional probability of making the maneuver. This will reflect “the real-world behavior that many drivers do not always change lanes, even if it is more advantageous to do so”. In addition, the following factors are considered in the DLC decisions:

- The intention of the leader in the current lane to change lanes or turn
- The intention of the target lane leader to turn or change lanes
- Whether or not the intended target lane leader is heavy vehicle
- Whether or not the current leader is a heavy vehicle

As for the adaptive acceleration behavior, the following cases are considered:

- “No change in acceleration- The adjacent gap is acceptable as is.
- The subject needs to accelerate – Either the total length of the adjacent gap is sufficient, but the lag gap is too small; or the total length of the adjacent gap is unacceptable, but the gap between the lead vehicle and its leader is acceptable.
- The subjects need to decelerate- Either the total length of the adjacent gap is sufficient, but the lead gap is too small; or the total length of the adjacent gap is unacceptable, but the gap between the lag vehicle and its follower is acceptable”.

Models for Autonomous Vehicle Control

In SHIVA, a situational awareness planner is implemented by including an effective navigation in traffic (SAPIENT) model for autonomous vehicle control

(Sukthankar, 1997). “SAPIENT contains several reasoning agents, which recommend actions based on their assigned element of situational awareness. Each recommended action will be then arbitrated based on the total votes received for each action and weighted by the reasoning agent’s influence weight” (Sukthankar, et al., 1997). As in MIXIC (Van Arem, et al., 2000), lane changing can be aborted in SAPIENT. The driver’s dissatisfaction with a speed lower than his desired speed is represented with a frustration function. Although revolutionary in its structure, models for autonomous vehicle control are not the best for implementing some panic behavioral characteristics at the operational level. They represent individualistic driver behavior but they are not based on parameters directly related to traffic conditions (for example, agents’ weights).

Having a robot car navigating the real-world was the main motivation for the PHAROS system project. A rule-based lane changing algorithm, ULYSSES, is included in that robot (Reece and Shafer, 1988; Reece and Shafer, 1993). This algorithm is based on MLC conditions with the DLC conditions to maintain desired speed. Both SAPIENT and ULYSSES make decisions based on observable features of the driver’s environment rather than direct knowledge of unknown parameters.

The ability of the autonomous vehicle to proactively change lanes defensively in reaction to another lane changing vehicle was illustrated in the Bayesian Automated Taxi- BATmobile. This kind of behavior could be frequent under panic conditions.

In summary, the main problem facing lane-changing models is calibration, due mostly to the nature of parameters used in these models. In the Gipps model, it is suggested that a 10 meters distance for the close “zone distance” gives good results for most simulations (Gipps 1986). However, this idea was extended by AIMSUM requiring a trial-and-error- iterative process to specify the length of the zones. In CORSIM, the calibrational difficulties are related to the urgency and risk values. These factors can not model cooperative driving and forced merging situations.

The models relying on utility-theory (for example, MITSIM) are based on many parameters that are not physical quantities. Their calibration needs an automated statistical procedure making the level of difficulty higher. As for the automated vehicles control, an additional complexity is added by the need to estimate the voting factors or the weights for particular agent components (SAPIENT).

The limited amount of trajectory data has made the validation of output components of lane changing models limited in its turn. This kind of data is even harder to get in panic conditions. On the other hand, there is no applicability of a particular model over a wide range of situations. This makes the validation problem harder to solve.

The key issue to be still studied in lane-changing models is their extensibility to include the effects of additional influencing factors such as weather conditions or heavy vehicle densities. This can be done by enhancing the mathematical forms in the mandatory/discretionary lane changing models. These

mathematical forms should improve “the set of nested *if...then* checks that determines when and how DLC and MLC actions are triggered and performed”. Still, this can not imitate the illegal and unsafe maneuvers to change lanes into the shoulder or median, especially high congestion situation.

2.4. Summary

A literature review of existing traffic models presented in this section aided in identifying key aspects of existing models that need to be addressed in the micro-simulation model formulated in Chapter 3. In most models reviewed in this chapter, such as the multi-regime and Gipps models, the main shortcoming is the assumption that drivers have safety limits or thresholds. During panic situations, drivers are willing take greater risks and consequently ignore safety constraints, potentially allowing accidents to occur and a higher level of congestion to follow. To relax this safety assumption, models needs to account for factors such as the allowable risk of driving maneuvers and the urgency of evacuation under a given extreme condition. Additionally, in lane-changing models both the lead and the lag values in the adjacent lane should be included into the decision process of a driver looking to execute a lane changing maneuver. Under extreme conditions the time required to change lanes and the delay between successive lane changes is typically small since sudden lane changes occur during extreme conditions.

The second major shortcoming of models reviewed in this chapter is the parameters used. These parameters typically have no behavioral explanation or meaning to them. In the model formulated in Chapter 3, parameters corresponding

to driver's and traffic characteristics that can be interpreted intuitively are introduced. Moreover, simply changing the values of these parameters during the is one way to capture some of the panic behaviors under extreme conditions. For example, the increase in the optimal velocity in the "desired measures" models can represent the increase of the velocities for aggressive drivers.

It can be seen that most of above remarks are observed in the Multi-Regime Models (Gipps, 1981) and in the Gipps Lane Changing Model (1986). Accordingly, the base model that is to be modified to account for drivers' behavior under extreme condition is the Gipps Car-Following Model. The following figure clarifies the logic behind this idea.

CHAPTER 3: A MICRO-SIMULATION MODEL

3.1. Introduction

In this chapter, modifications to the Gipps model mentioned in Chapter 2 are proposed in an attempt to better represent certain aspects of driver behavior under extreme conditions. As mentioned previously, a range of extreme conditions, associated with different events, may be encountered; these may be different in nature and may elicit different responses depending on the specific situation. The type of extreme conditions presented and discussed in this chapter are those that impose a sense of urgency on the drivers. Accordingly, these drivers aim to evacuate a given area in a relatively small amount of time, which may cause chaos and disorder, and in turn impede the progress of the evacuation. Under these extreme conditions, drivers tend to be more aggressive, or they may lose focus and get lost in unfamiliar areas of the network.

Since the aim is to model and capture panic behavior at the individual driver level, microscopic models of driver behavior are considered. This chapter presents a static (time independent) microscopic model formulation of traffic flow that incorporates certain elements of driver behavior under extreme conditions. The next section presents and discusses the car-following component. The following section presents and discusses the lane-changing component. The final section provides concluding remarks.

3.2. Car-Following Model

The Gipps model (1981) is intended by its developer as a “general multi-regime” car-following model. This model is selected as a starting point for modification to capture certain aspects of panic behavior of drivers under extreme conditions. This model was selected for three reasons. First, it can be applied to both car-following and free-flow conditions, and consequently could potentially capture panic behavior under both congested and uncongested traffic situations. Second, the model contains parameters, corresponding to characteristics of drivers and vehicles, that have relatively simple and intuitive behavioral interpretation. These parameters can be fairly easily modified to approximate the twelve driver panic behavioral characteristics listed in Chapter 1. Third, the Gipps model is an operational microscopic model, that can be readily implemented and incorporated in a flow simulation framework. Ultimately these behaviors can be then aggregated to see the effect of extreme conditions on a macroscopic level.

The Gipps model is modified to accommodate behavior under extreme conditions by (i) relaxing some constraints in the model, such as a safety threshold at the individual-driver level (which may then give rise to accidents or other types of incidents); (ii) altering the structure of the equations in the model (by either completely altering the structure of the equations or adding or removing variables); and (iii) changing the values of the input variables of the model, as a way of representing new traffic situations in different locations.

The model aims to capture panic behavior on a 2-lane straight freeway segment of length L . On this segment, N vehicles are loaded during an interval of

simulation time T . The vehicles are all identical with the same vehicle length S . The main assumption made is that each driver has a desired velocity V_n that he/she tries to maintain. The variables included in the simulation model are listed and described below:

1. \mathbf{a}_n (m/s^2): the maximum acceleration that the driver of vehicle n wishes to undertake. Under extreme conditions, drivers typically are willing to apply higher acceleration rates than under normal conditions, causing irregularities and possible instabilities in traffic flow patterns. . This variable is drawn from a truncated Gaussian-shaped (Normal) distribution with a given mean and variance. The truncation is performed through a range variable and it is based on the value of the mean chosen during the sensitivity analysis. The aim of this truncation is mainly to deal with negative values and the different ranges are presented in Chapter 4. Although drivers may act in a chaotic manner under extreme conditions, there may still exist a distribution describing the variation of this behavior across drivers.
2. \mathbf{b}_n (m/s^2) is the most severe braking that the driver of vehicle n wishes to undertake ($b_n < 0$). This increase in the braking rate relative to normal conditions is based on the hypothesis that under extreme conditions, drivers tend to have higher braking rates or increased use of emergency braking. This value is also drawn from a truncated normal distribution with a given mean, variance and range at the beginning of the simulation.

As mentioned earlier, the ranges of all the normal distributions are specified in Chapter 4.

3. s_n (m) is the effective size of vehicle n , which consists of its physical length plus a margin (headway) into which the following vehicle is not willing to intrude, even when at rest. This margin (headway) is all but ignored during aggressive driving; drivers tend to be tailgated by their followers. Thus in this study, s_n is simply the vehicle size plus a minimal margin of about ten to twenty centimeters. The value of s_n is assumed to be constant for all vehicles (S).
4. V_n (m/s) is the speed at which the driver of vehicle n wishes to travel. The value is randomly chosen from a probabilistic mixture of two normal distributions. For the first distribution, the mean is higher than the suggested mean in the Gipps Model. For the second distribution, the mean is lower than the suggested Gipps mean. This differential in means suggests that some aggressive drivers seek to increase their desired velocity under panic conditions, hoping to evacuate the area affected. However, other drivers tend to slow down. They are either not panicking yet, or they may be lost or quasi-paralyzed with little knowledge of what to do. This choice is consistent with an illustration by Daganzo (1999) of the disruptions and the irregularities in traffic flow resulting from velocity differentials (idealized as two classes of drivers, so-called “slugs” versus “rabbits”). It should be noted that the relative composition of the driver population into each of the two types is itself a parameter reflecting a

particular panic situation, and is a worthwhile subject of investigation. Furthermore, the two-class representation is only a simplified representation of a richer population mix with many underlying classes.

5. $\mathbf{x}_n(\mathbf{t})$ (m) is the location of the front of vehicle n at time t of the simulation.
6. $\mathbf{v}_n(\mathbf{t})$ (m/s) is the speed of vehicle n at time t .
7. τ_n (s) is the apparent reaction time. It is also drawn from a truncated normal distribution. The increase in the number of moving stimuli, such as flying debris during fire accidents or moving trees during hurricanes, will likely cause a decrease of sensitivity to the main stimulus. Drivers will lose some of their focus on the surrounding vehicles. Accordingly, their reaction time will increase and so does the mean of the normal distribution adopted. (Evans and Rothery, 1977).
8. D_n (m) represents the distance a driver is willing to travel beyond the safety threshold. The safety threshold indicates the distance between the driver and the leading vehicle at which the driver would start decelerating so that his vehicle can come to a complete stop before hitting the preceding vehicle. This value is added to the model to allow potential accidents to be generated. It reflects the willingness of a driver to take a risk. The value of D_n for each vehicle n is drawn from a truncated normal distribution. When this value is positive, the driver is willing to take risk and this may increase the probability of causing an accident. If this value is negative, the driver prefers to stay within the safety margin so he/she can come to a stop without hitting any other vehicle.

Two main conditions need to be satisfied in this model. The first condition, which concerns the acceleration-deceleration of individual drivers, requires that a vehicle n not exceed its driver's desired speed; its "free" acceleration should first increase with speed as engine torque increases, then decrease to zero as the vehicle approaches the desired speed. This condition is purely descriptive and emulates driver behavior or vehicular movement under free-flow situations. This condition is expressed in the relationship below:

$$v_n(t + \tau_n) \leq v_n(t) + 2.5a_n \tau_n \left(1 - \frac{v_n(t)}{V_n}\right) \left(0.025 + \frac{v_n(t)}{V_n}\right)^{1/2} \quad (1)$$

The above expression has two important behavioral implications. The first implication is reflected by the term $\left(1 - \frac{v_n(t)}{V_n}\right)$. This term is equal to zero when the actual velocity of the driver is equal to his desired velocity. Accordingly, $v_n(t + \tau_n) = v_n(t)$; the velocity at time $t + \tau_n$ is to remain the same. The second implication is based on the term $\left(0.025 + \frac{v_n(t)}{V_n}\right)^{1/2}$. This term ensures that the change between $v_n(t)$ and $v_n(t + \tau_n)$ is not linear over time with the introduction of the power term $1/2$. Since at free flow conditions, and according to the main assumption of the model, drivers always tend to accelerate and increase their velocity to their desired speed, the deceleration term b_n is not found in Expression (1). Only a_n and τ_n are involved. The constant parameters (2.5 and 0.025) are the result of an envelope to a plot of instantaneous speeds and accelerations obtained from an instrumented car traveling down an arterial road in moderate traffic

(Gipps, 1981). These parameters are not modified in the present study, because panic behavior is reflected only through the vehicle-related parameters.

The second condition is related to congested traffic situations. It initially states that the driver of vehicle n must ensure that $x'_{n-1} - s_{n-1}$ exceeds x'_n , where x'_{n-1} is the location of the preceding vehicle $n-1$ when it comes to rest after it starts braking as hard as desirable;

s_{n-1} is the length of this vehicle with its minimal margin; and

x'_n is the location of the vehicle of interest when it comes to rest after reacting at time $t + \tau_n$, where τ_n is the reaction time.

Specifically, the expression $x'_{n-1} - s_{n-1} > x'_n$ indicates that when a driver starts decelerating so his vehicle will stop at a given location x'_{n-1} , the following vehicle will decelerate and come to rest before hitting the rear end of the preceding vehicle. This condition satisfies safety regulations, and accordingly will prevent accidents. However, in extreme conditions, with more aggressive driving patterns, some drivers are willing to take greater risk and are hence more prone to accidents/crashes. For that purpose, the term D_n is subtracted from $x'_{n-1} - s_{n-1}$. In this case, even if $x'_{n-1} - s_{n-1} - D_n > x'_n$, the distance between two vehicles can be negative and an accident may be generated.

If the safety regulations are to be kept, the following relations are to be respected:

$$x'_{n-1} = x_{n-1}(t) - \frac{v_{n-1}(t)^2}{2b_{n-1}} \quad (2)$$

$$x'_n = x_n(t) + [v_n(t) + v_n(t + \tau_n)] \frac{\tau_n}{2} - \frac{v_n(t + \tau_n)^2}{2b_n} \quad (3)$$

and

$$x'_{n-1} - s_{n-1} \geq x'_n \quad (4)$$

After introducing D_n , the new equation will be:

$$x_{n-1}(t) - \frac{v_{n-1}(t)^2}{2b_{n-1}} - s_{n-1} - D_n \geq x_n(t) + [v_n(t) + v_n(t + \tau_n)] \frac{\tau_n}{2} - \frac{v_n(t + \tau_n)^2}{2b_n} \quad (5)$$

Combining (1) and (5), the final expression for the velocity of vehicle n at time $t + \tau_n$ is:

$$v_n(t + \tau_n) = \min \left\{ v_n(t) + 2.5a_n \tau_n \left(1 - \frac{v_n(t)}{V_n}\right) \left(0.025 + \frac{v_n(t)}{V_n}\right)^{1/2}; \right. \\ \left. b_n \left(\frac{\tau_n}{2}\right) + \sqrt{\frac{b_n^2 \tau_n^2}{4} - b_n \left[2(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t) \tau_n - \frac{v_{n-1}(t)^2}{b_{n-1}} + D_n\right]} \right\} \quad (6)$$

It should be noted that the initial equation of the (unmodified) Gipps Model is:

$$v_n(t + \tau_n) = \min \left\{ v_n(t) + 2.5a_n \tau \left(1 - \frac{v_n(t)}{V_n}\right) \left(0.025 + \frac{v_n(t)}{V_n}\right)^{1/2}; \right. \\ \left. b_n \tau + \sqrt{b_n^2 \tau^2 - b_n \left[2(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t) \tau - \frac{v_{n-1}(t)^2}{b_{n-1}}\right]} \right\} \quad (6')$$

The second term in the equation allows for higher velocities. This is due to the safety margin θ taking a value of $(\tau / 2)$, as introduced in equation (5). The above expressions show that in the original Gipps model, the apparent reaction time τ is taken as constant for all vehicles, and that the safety margin θ would allow the

driver a margin of error making or possible additional delay during which he will be traveling at $v_n(t + \tau)$, before reacting to the vehicle ahead. Taking this delay into account, drivers can travel at higher velocities with greater spacing between them and the preceding vehicle. Equation (5) in the original Gipps Model is:

$$x_{n-1}(t) - \frac{v_{n-1}(t)^2}{2b_{n-1}} - s_{n-1} \geq x_n(t) + [v_n(t) + v_n(t + \tau)]\frac{\tau}{2} + v_n(t + \tau)\theta - \frac{v_n(t + \tau)^2}{2b_n} \quad (5')$$

Under extreme conditions, the term θ is removed since drivers do not allow for this margin of safety, and errors would be more frequent. This will result in lower velocities and accordingly, more congested situations.

The above model still faces several limitations in its ability to represent car following behavior under all possible situations. The main advantage over other models is that it allows for the occurrence of accidents because it is not arbitrarily constrained by the safe-headway concept. This is captured primarily through the factor D_n included in the model. To deal with this issue, every time the headway between two vehicles is less than zero, the speed of both vehicles will be set to zero. However, this will limit the accident occurrence to one lane only.

The above car following model is aimed to capture the highest number of the twelve panic behavioral characteristics discussed in chapter 1. Table 3.1 shows the intended characteristics and how they are covered.

The above model only captures one dimension of the driving task on a multi-lane highway. The only possible maneuver is either to increase or decrease

a driver's speed. Another critical dimension is the ability to change lanes. The next section discusses a possible model of lane-changing behavior.

Panic Behavioral Characteristic	Model Modification
Tailgating, decrease in headways	Decrease in the effective vehicle size s_n
	Removing safety margin θ
Increase in velocity when possible	Increase in desired velocity V_n for aggressive drivers (mean in normal distribution)
higher acceleration without smooth velocity change	Increase in acceleration rate parameter a_n
Higher Deceleration rate and emergency braking	Increase in deceleration rate parameter b_n (in absolute value)
Higher Velocity Variance due to the presence of aggressive drivers and drivers being lost or still rationalizing their decisions	Drawing Velocities from two normal distributions with higher variance
Increase in accidents number	Introduction of the parameter D_n

Table 3.1: Model Modifications Accounting for Panic Behavioral Characteristics

3.3. Lane-Changing Model

In addition to the car-following model, Gipps offers another model that explains the structure of lane-changing decisions. Although well detailed, his model discusses complex objectives behind lane changing behavior that do not apply to the basic situation of this study (Gipps, 1984). Moreover, lane changing is based on the gaps offered by traffic in the adjacent lanes. Accordingly, accepting these gaps will be related to the relative speed and acceleration of both the leading and the lagging vehicle in the adjacent lane. Gipps' model takes into account only the properties of the leading vehicle.

In this study, driver's logic to change lanes is based on the answer to the three following questions:

- Is it desirable to change lanes?
- Is it possible to change lanes?
- Is it necessary to change lanes?

Lane-changing decisions are strongly related to the desirable speed at which a driver wishes to travel. A driver traveling at a speed less than his desirable speed will seek to increase his speed in the same lane. If another vehicle is in the way (space headway between the two vehicles is less than 5 meters, which is the average length of a car), the following driver will consider changing lanes. However, the driver must check first if this maneuver is possible with the gaps offered in the adjacent lane. Checking these gaps is a procedure to be specified as part of the lane changing model. Figure 3.1 clarifies the logic behind combining the lane changing model and the car following model together.

On the other hand, it was found that the average lead or lag times for all traffic conditions are almost equal (FHWA, 1969). Accordingly, it may be suggested that neither the lead nor the lag dominates the gap-acceptance decision in lane-changing. Therefore, both the leading and the lagging vehicles in an adjacent lane are objects of interest in this study.

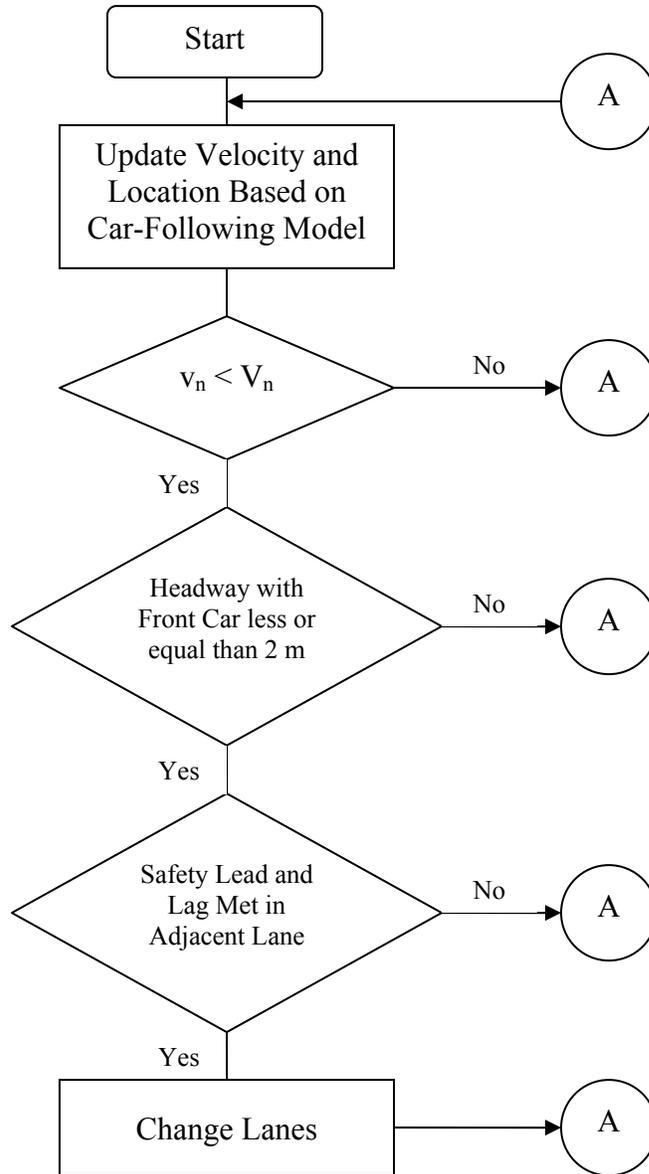


Figure 3.1: Logic for combining Car Following and Lane Changing Models

The theoretical estimate of the minimum safe lead value based an assumed desirable deceleration rate and an average braking perception/reaction time is given by the following equation:

$$L_1 = v_n(t)\tau_n + \frac{v_n(t + \tau_n)^2}{|2b_n|} - \frac{v_m(t + \tau_n)^2}{|2b_m|} \quad (7)$$

where:

m = subscript for a leading vehicle in destination lane

L_1 = safe “lead” distance for lane changing (m)

$v_n(t + \tau_n)$ = speed of lane-changing vehicle n (m/sec)

$v_m(t + \tau_m)$ = speed of leading vehicle m in destination lane (m/sec)

b_n = deceleration rate vehicle n can sustain (m/sec²)

b_m = deceleration rate vehicle m can sustain (m/sec²)

τ_n = apparent reaction time for vehicle n (braking perception/reaction time) (sec)

τ_m = apparent reaction time for vehicle m (braking perception/reaction time) (sec).

With the same logic, the theoretical estimate of the safe lag value is:

$$L_2 = v_{m+1}(t)\tau_{m+1} + \frac{v_{m+1}(t + \tau_{m+1})^2}{|2 b_{m+1}|} - \frac{v_n(t + \tau_{m+1})^2}{|2 b_n|} \quad (8)$$

where:

$m+1$ = subscript for a lagging vehicle in destination lane

L_2 = safe “lag” distance for lane changing (m)

$V_n(t + \tau_n)$ = speed of lane-changing vehicle n (m/sec)

$v_{m+1}(t + \tau_{m+1})$ = Speed of lagging vehicle $m+1$ in destination lane (m/sec)

b_n = deceleration rate vehicle n can sustain (m/sec²)

b_{m+1} = deceleration rate vehicle m can sustain (m/sec²)

τ_n = apparent reaction time for vehicle n (braking perception/reaction time) (sec)

τ_{m+1} = apparent reaction time for vehicle $m+1$ (braking perception/reaction time)

(sec).

However, it is suggested that both lag and lead distances are over-estimated (FHWA, 1969). The use of different parameters during extreme conditions will help deal with this subject. First, the higher deceleration rates in absolute value will decrease the safe leads and lags to be accepted. This is expected during panic behavior especially on the part of aggressive drivers, since their patience is limited and they tend to accept shorter gaps as mentioned in Chapter 1. For clarification purposes, Figure 3.2 is presented.

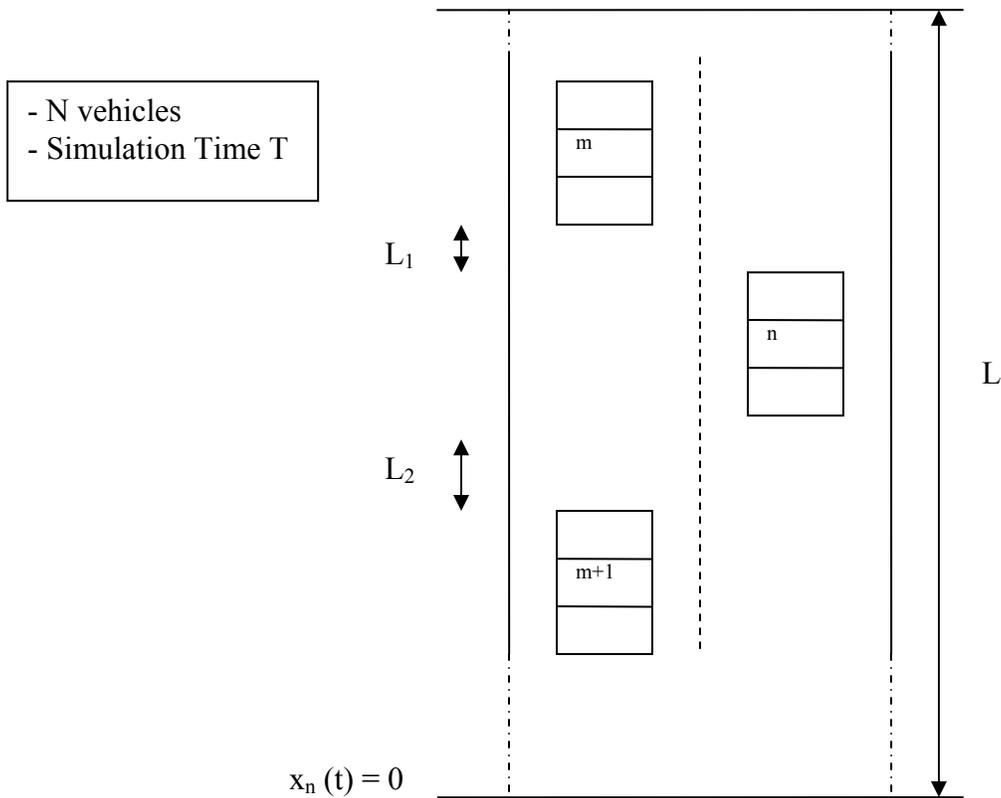


Figure 3.2: Lane Changing Decision concept

It should be noted that accidents will be still possible in this lane changing model due to the duration required for the lane-changing maneuver. This will be discussed in the implementation section in chapter 4. The general idea is that if

the lane-changing maneuver is seen as possible, the respective locations of vehicles n , m , and $m+1$ are computed in the target lane after a given lane changing time. This time is also drawn from a normal distribution varying from one driver to another. Moreover, to capture sudden lane changing, lane changing time is reduced to have a mean of 2 seconds, a value that is further studied in the sensitivity analysis. If $x_m(t) - x_{m+1}(t) - s_m$ is less than or equal to s_n , the respective velocities of the three vehicles are set to be equal to zero, indicating the occurrence of an accident in that lane. It may be suggested that accidents due to lane changing may block both lanes of travel. However, in panic situations, drivers tend to use shoulders, even pedestrian sidewalks to escape this kind of accident.

3.4. Summary

The above model represents an attempt to modify Gipps' Car - Following Model to capture certain aspects of driver behavior under panic conditions. It is complemented with a lane changing model for a more complete elementary representation of traffic interactions in a simple two-lane highway section. This model relies primarily on the modification of existing parameters of the Gipps' model formulation and the introduction of a new risk-based parameter D_n . The next chapter presents extensive sensitivity analysis of the model and of traffic performance vis a vis these parameters; of particular concern is the instability introduced in the traffic system due to the possible presence of accidents.

As noted, this model represents a first attempt to deal with several of the panic factors discussed in the previous chapters, but not all of them. A comprehensive treatment of all panic factors requires capturing behavior under all sorts of extreme conditions, even those that does not involve urgency issues, such as heavy weather situations. Such a degree of completeness remains beyond the ambition of the present study.

CHAPTER 4: MODEL IMPLEMENTATION AND SIMULATION RESULTS

4.1. Introduction

Setting the theoretical background of a traffic model differs from building and testing this model. This task requires a considerable amount of coding effort with an understanding of the qualitative effect of the different parameters introduced in chapter 3 on the drivers' behavior and the resulting aggregate traffic characteristics.

In Chapter 4, the first section describes the procedures followed to implement the model. Before studying the output results, the model is partially validated using actual data collected for the US Federal Highway Administration's Next Generation Simulation (NG-SIM) project conducted by Cambridge Systematics, Inc.. Once validated, the different results obtained are analyzed and linked to the different parameter values used as input. For that purpose, a micro and a macro sensitivity analysis are presented to discuss the possible panic behavioral characteristics captured by the modified model.

4.2. Model Implementation

In this study, the C++ language was adopted to code and implement the modified Gipps model discussed in Chapter 3. After defining the necessary simulation "Libraries", the different functions and variables used in the program are declared. Some of the functions and variables are only related to the graphical

output and sensitivity analysis properties. However, the only ones discussed in this section are those related to the core of the simulation model. From this family, the main function declared is the function “normal ()” that returns a normal distribution of a given variable after providing it a mean, a standard deviation and a range. The “range” is a variable that restricts (truncates) the generated distribution to $[\text{Mean}-\text{Factor}/2; \text{Mean}+\text{Factor}/2]$. This allows greater control on the normally distributed parameters, especially when dealing with boundary conditions. For example, “range” will not allow negative velocities when declaring the two distributions of the drivers’ desired velocities. On the other hand, the variables used in the core simulation model are either input/generated variables or output/computed variables. The input variables can be either kept as default values or they can be changed by the user. The main variables used in the simulation are presented in Tables 4.1 and 4.2.

Variable Type	Symbol	Description
Double (double)	headway	Space Separation Between Car n and Car n-1 (m)
Double (double)	x	Location of front vehicle n (m)
Double (double)	v	Velocity of vehicle n (m/s)
Integer (int)	crash	Binary Variable Indicating the Presence of a Crash
-	-	Density at each Time Step per Km Segment per Lane (veh/km/lane)
Array of Integer (int)	QL0[i]	Flow per Simulation Time at Lane 0 at the End of Km i of the road length (veh/simulation time/lane)
Array of Integer (int)	QL1[i]	Flow per Simulation Time at Lane 1 at the End of Km i of the road length (veh/simulation time/lane)
Array of Double (double)	UL0[i]	Cumulative Space Mean Speed at Lane 0 on Km i of the road length (m/s)
Array of Double (double)	UL1[i]	Cumulative Space Mean Speed at Lane 1 on Km i of the road length (m/s)
Array of Integer (int)	UL0c[i]	Counter of Vehicles involved in the space mean speed calculation at Lane 0 on Km i
Array of Integer (int)	UL1c[i]	Counter of Vehicles involved in the space mean speed calculation at Lane 0 on Km i

Table 4.1: Output/Computed Variables Used in the Simulation Program

Variable Type	Symbol	Description
Integer (int)	T	Total Number of Time Steps (multiple of 0.1s)
Integer (int)	Time	Current Time Step
Integer (int)	N	Total Number of Cars
Double (double)	L	Total Road Length (m)
Double (double)	meanacc	Mean of the Acceleration Distribution (m/s^2)
Double (double)	stdacc	Standard Deviation of the Acceleration Distribution
Double (double)	rangeacc	Range of the Acceleration Distribution
Double (double)	meandecc	Mean of the Deceleration Distribution (m/s^2)
Double (double)	stddecc	Standard Deviation of the Deceleration Distribution
Double (double)	rangedecc	Range of the Deceleration Distribution
Double (double)	meanVd_1	Mean of the Low “Slugs” Desired Velocity (m/s)
Double (double)	stdVd_1	Standard Deviation of the “Slugs” Desired Velocity
Double (double)	rangeVd_1	Range of the “Slugs” Desired Velocity
Integer (int)	percentVd_1	Percent of “Slug” Among the Drivers
Double (double)	meanVd_2	Mean of the High “Rabbits” Desired Velocity (m/s)
Double (double)	stdVd_2	Standard Deviation of the “Rabbits” Desired Velocity
Double (double)	rangeVd_2	Range of the “Rabbits” Desired Velocity
Integer (int)	percentVd_2	Percent of “Rabbits” Among the Drivers
Double (double)	meanrisk	Mean of the Risk Factor D_n (m)
Double (double)	stdrisk	Standard Deviation of the Risk Factor D_n
Double (double)	rangerisk	Range of the Risk Factor D_n
Double (double)	meanRT	Mean of the Reaction Time τ_n (s)
Double (double)	stdRT	Standard Deviation of the Reaction Time τ_n
Double (double)	rangeRT	Range of the Reaction Time τ_n
Double (double)	meanLCT	Mean of the Lane Changing Time LCT (s)
Double (double)	stdLCT	Standard Deviation of the Lane Changing Time LCT
Double (double)	rangeLCT	Range of the Lane Changing Time LCT
Double (double)	StartV	Starting Velocity When Vehicle Enters Simulation (s)
Integer (int)	departure	Departure Time of Entering Vehicle (s)
Integer (int)	carID	ID car of the car entering the simulation
Integer (int)	lane	Binary Variable indicating in which the vehicle exists
Double (double)	s	Vehicle effective length (m)

Table 4.2: Input/Generated Variables Used in the Simulation Program

It should be noted that the densities are calculated through general purpose variables that are directly printed into output files. Moreover, some variables are used in association with other variables and are not mentioned in the previous tables. For example, the variable “reaction” (integer) is not described in Table 4.2.

It is only used to map the variable RT to the corresponding time step (multiple of 10). The default values of the input parameters are given in Table 4.3.

Variable	Default Value
T	2000 Time Steps (200 s)
N	50 vehicles
L	2000 m
meanacc	2 m/s ²
stdacc	0.3 m/s ²
rangeacc	2 m/s ²
meandecc	-3 m/s ²
stddecc	0.3 m/s ²
rangedecc	2 m/s ²
meanVd 1	13.33 m/s
stdVd 1	3.2 m/s
rangeVd 1	18 m/s
percentVd 1	10 %
meanVd 2	35.55 m/s
stdVd 2	4 m/s
rangeVd 2	52 m/s
percentVd 2	90%
meansik	15 m
stdrisk	5 m
rangerisk	20 m
meanRT	1 s
stdRT	0.4 s
rangeRT	1.4 s
meanLCT	2.5 s
stdLCT	0.5 s
rangeLCT	1 s
StartV	17.77 m/s

Table 4.3: Default Values for Input Parameters

The user of the program can choose between generating a totally new simulation with newly produced values of the random variables, or between loading an existing file to re-simulate. This is offered for sensitivity analysis purposes so the user can study the effect of the change in a particular variable keeping the other randomly distributed variables constant. If the user chooses to generate a new simulation, the default values of the input parameters presented in

Table 4.3 could be changed. The user could also save the simulation file before loading it. On the other hand, in sensitivity analysis mode, to the user has the option of loading one of the saved files and changing any of the desired parameters presented in Table 4.3. The new file can be resaved and loaded for simulation. The only variable that cannot be changed in the sensitivity analysis mode is the number of cars N. This is due to the fact that the memory allocation for a specific number of “classes” is already pre-specified in the saved files. In other words, in the simulation code, each vehicle is a class “car”. This class is associated with the needed vehicle-specific characteristics described previously. Moreover, it is associated with two pointers:

- 1- Car*previous pointing to the leading car in the same lane
- 2- Car*next pointing to the lagging car in the same lane

During the simulation, the flow on a given lane is represented by a doubly linked list. In both “sensitivity analysis mode” and “new simulation mode”, the user should specify the type of data output desired before running the simulation. If the user chooses “micro” mode, two types of output files are obtained: The “CRASH.txt” file gives the location of every crash, the lane in which it occurred, and the cars involved; the “CARS.txt” file gives the location, the velocity, the headway and the lane in which the vehicle is, at every time step and for every vehicle. If the user chooses the “macro” mode, three different files are generated. The first one is “CRASH.txt”. The other two files are “LANE0.txt” and “LANE1.txt”. For each lane, these provide the space mean speed and the flow on

every Km of the road length. Moreover, they include the density at every time step for each of the 1 Km segments.

The “main” component of the simulation code is divided into the following categories:

a- Declare and Initialize:

In this part of the simulation, three types of doubly linked lists are used. The first type is a departure list in which the vehicles are ordered by increasing departure time. The second type consists of two lane lists that are representative of the vehicles on each lane while they are still within the specified road length L. These vehicles are only part of the lane lists as long as their departure time is reached and the total simulation time is not over. Finally, the two queue lists are created to store the vehicles to the next time step as long as the preceding one did not fully enter the road segment. It should be noted that the departure times of the vehicles are uniformly distributed across the total simulation time.

b- Graphics:

An INTRO provides the front page set up. A LOAD FILE presents the code necessary to load existing files to simulate. The SENSITIVITY ANALYSIS and the NEW SIMULATION are the two procedural modes of the program.

c- Initialize Cars:

In this part, all the vehicle-specific characteristics are initialized as presented in Table 4.4.

Vehicle-specific parameter	Initial Value
s	5 m
x	0 m
v	17.78 m/s (=startV)
l	0
headway	“blank character”
crash	0

Table 4.4: Initial Values for Vehicle-Specific Parameters

The “carID” is assigned in increasing order from 1 to N while generating the vehicles. As for the other characteristics, their value is randomly generated from the corresponding truncated normal distribution.

d- Save and Launch Simulation

e- File Initialization:

The file Initialization is the part in which all the output files mentioned before are fully defined so the corresponding output values are imprinted in them.

f- Begin Simulation:

In this section, the operations are repeated inside an incremental loop. The following steps are followed:

1- Screen Display

2- Feed New Car Entering:

According to the departure list, the cars are fed into the two lane lists L0 and L1. The appropriate lane is chosen based on the binary value l that is randomly generated based on the rand() function. If the preceding vehicle did not fully enter the lane when the departure time of the following vehicle occurs, this vehicle will wait in the queue list (L0q or L1q) until the preceding car is fully inside the road segment L.

3- Car Following Decision:

The Car Following Decision discussed in chapter 3 is implemented in this section.

4- Lane Changing Decision:

As in the Car Following Decision section, the logic of the Lane Changing discussed in chapter 3 is implemented here. On the other hand, it should be noted that the lane changing maneuver is not executed until $LCT*10$ time steps pass.

5- Remove Entering Vehicles:

This operation is executed if the car position exceeds the total road length. If the simulation time is over, the last output values computed are saved in the corresponding output files.

6- Headway and Crash Detection:

In this section, at every time step, the vehicle headway is computed after updating its location. Moreover, if a vehicle's headway is less than 5 meter, a crash is detected. The crash parameter is 1 instead of zero and the vehicle specific parameters are frozen. The vehicle's velocity is dropped to zero following a deceleration rate of -6 m/s^2 .

7- Save Data:

As the incremental loop continues, the output variables are saved to temporary files.

g- Output Data:

The Data saved in the temporary files are imprinted into the pre-specified output files.

At the end of the simulation all the functions declared at the beginning are defined. The normal function (normal ()) is based on the polar method improved from the Box and Muller method by Atkinson and Pearce (1976). Figure 4.1 summarizes the steps adopted to implement model.

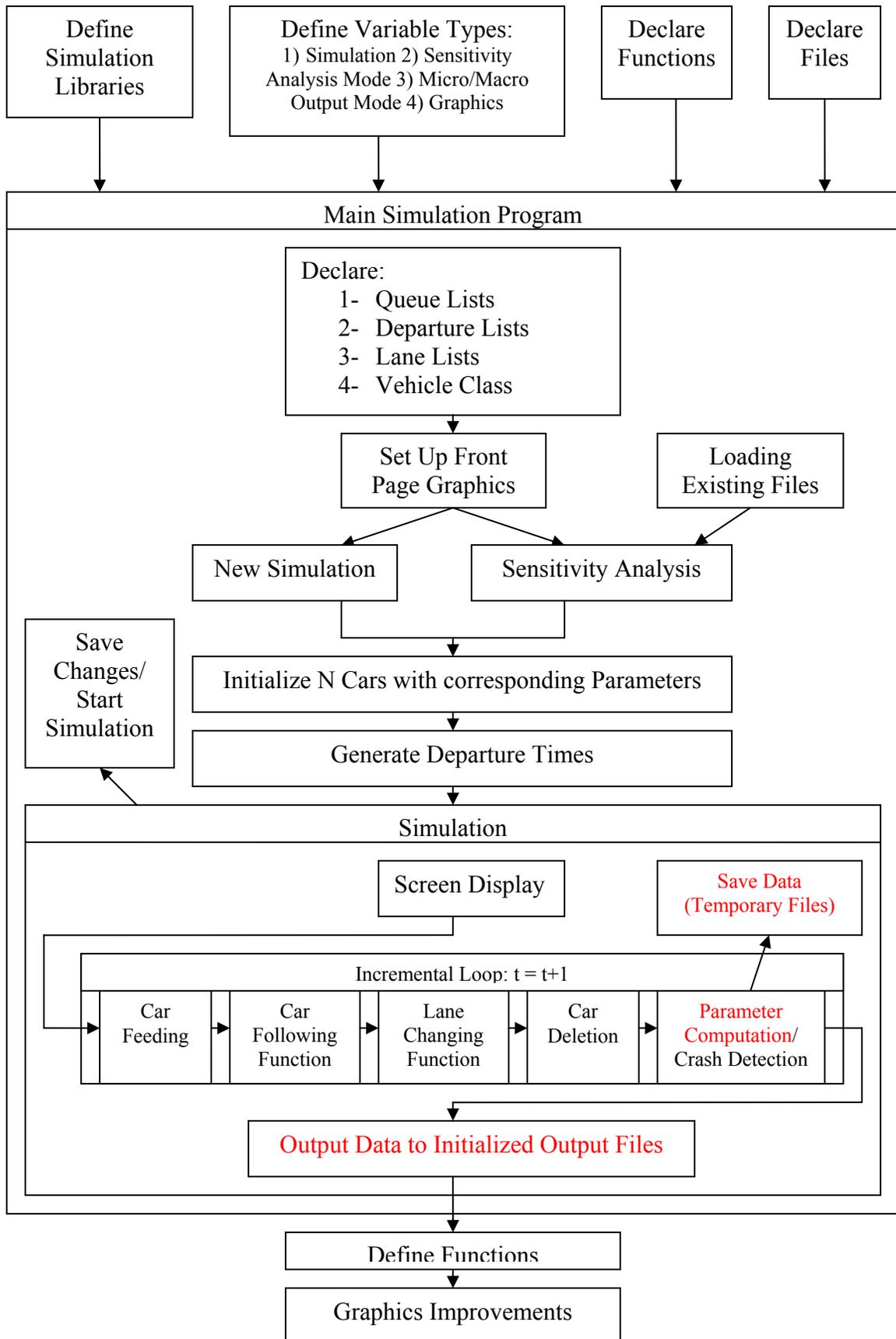


Figure 4.1: Model Implementation

Once implemented, the model should be tested against real-life data before being assessed for its ability to model driver behavior under extreme conditions. The next section aims to compare the output results obtained from a specific set of input parameters with available data.

4.3. Validation

The data used for validating the modified Gipps model are provided through the US FHWA’s Next Generation Simulation (NGSIM) project conducted by Cambridge Systematics, Inc.. The data set includes trajectory data for 4733 vehicles over one-half hour (2:35 p.m. – 3:05 p.m.) on December 3, 2003. The data are collected on Interstate 80 in Emeryville, California, USA by researchers at the University of California, Berkeley. The study area is a straight 2950 feet freeway section consisting of six lanes (lane 1 through lane 6) with an on-ramp (lane 7) at the beginning of the section and an off-ramp (lane 8) at the end. Figure 4.2 illustrates the study area more clearly. The x and y coordinate location is captured every 1/15th second. These data are also processed so aggregate traffic measures such as flows and space-mean speeds are calculated over the time period of the study. Table 4.5 and 4.6 show these results.

Time Period	Flow (vph)	Space Mean Speed (m/s)
2:35 p.m. - 3:05 p.m.	9466	25.62804

Table 4.5: Aggregate Results Summary for the Entire Section

Measure	Lane						Average
	1	2	3	4	5	6	
Flow (vph)	1744	1764	1406	1540	1506	1506	1578
Space-Mean Speed	29.97134	24.95984	24.5949	24.75938	24.5692	25.02666	25.62804

Table 4.6: Aggregate Results for Each Lane

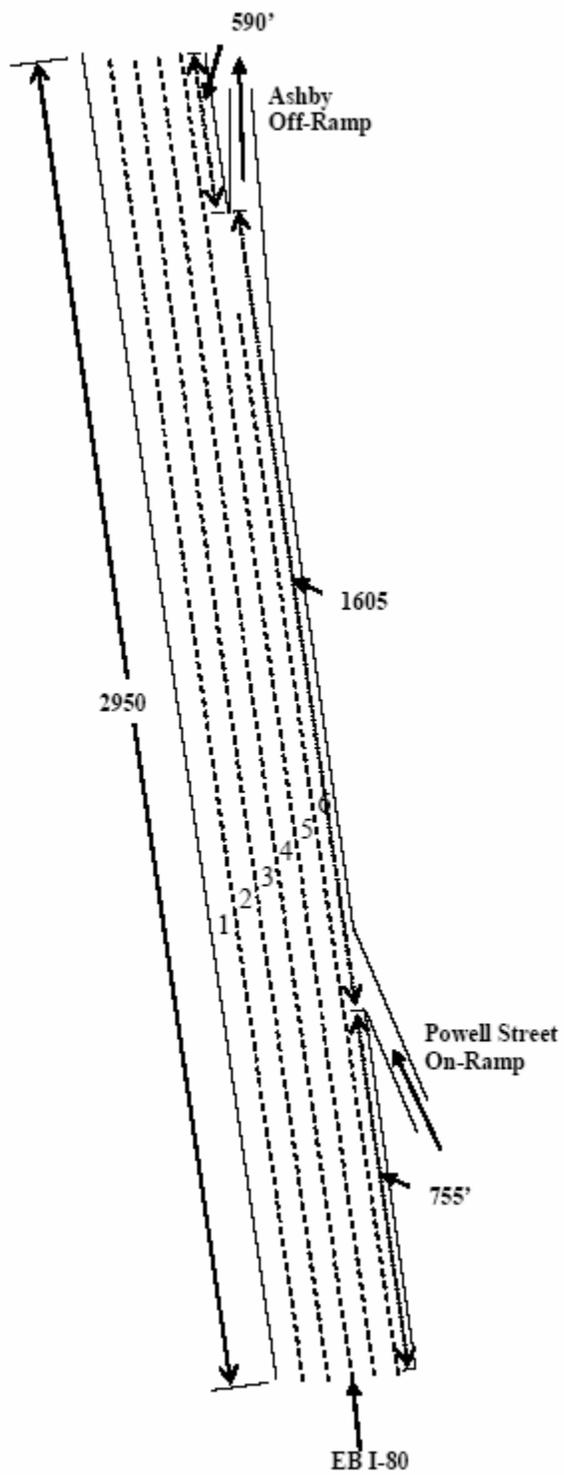


Figure 4.2: Schematic of the Study Area
 (Selected from NGSIM BHL Data Analysis, Summary Report (2004))

The trajectories of the first 50 vehicles entering the freeway section are mapped on the time space diagram shown in Figure 4.3.

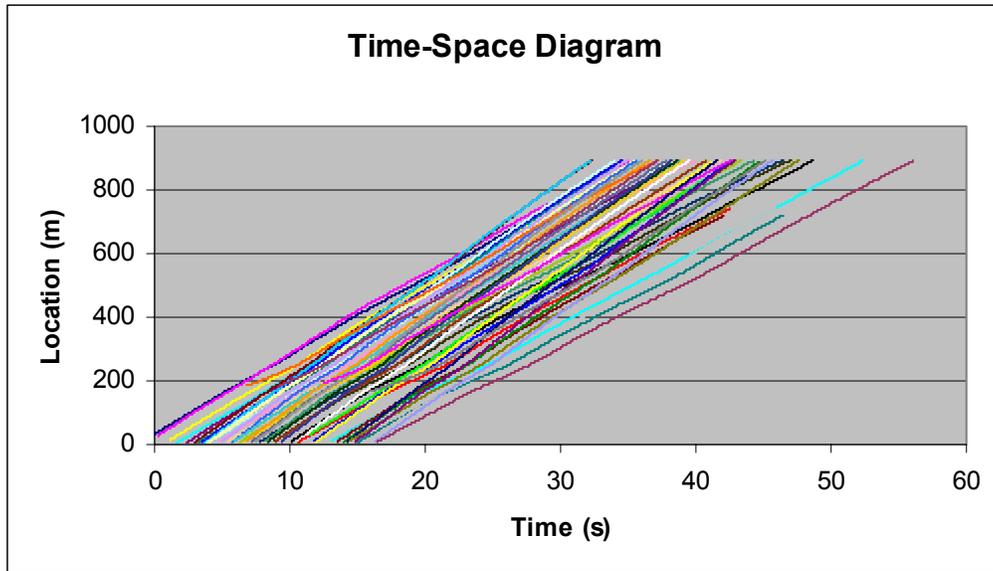


Figure 4.3: Time-Space Diagram of the First 50 Vehicles Entering the Study Area

The velocity distribution of the same vehicles is shown below.

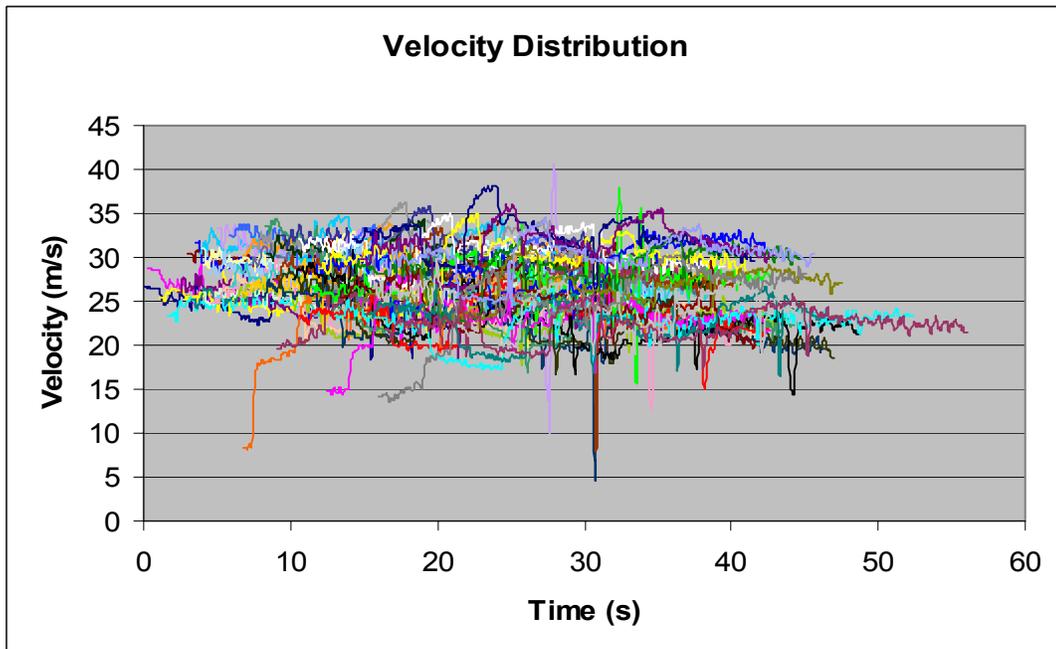


Figure 4.4: Velocity Distribution of the First 50 Vehicles Entering the Study Area

To pursue this validation effort, some of the limitations of the implemented simulation program should be addressed. The first limitation is related to the memory constraints faced in the particular version of the C++ language (Borland) used in this initial implementation. The maximum number of vehicles that can be handled in the simulation program is 600. Choosing a simulation scenario with 450 vehicles (N), the total simulation time should be 514 seconds; the ratio of 4733 vehicles over a 30 minutes data recording time is conserved. This ratio matching takes into account the second limitation to be faced. This limitation is associated with the number of lanes that can be handled by the suggested model. As mentioned earlier, the study area is a 6-lane freeway section, an on-ramp, and an off-ramp. However, the implemented simulation program only considers a two-lane highway section with simplified features. For that reason, the model validation will be based on the average data collected over the total number of lanes and the lane specific results.

The input parameters used for validating the suggested model are summarized in Table 4.7. These parameters assume normal conditions. The initial Gipps model is then used with the assumption that there is only one velocity distribution Vd_1 that occurs 100% of the time. Moreover, the accidents are eliminated by assigning a zero risk factor. The rest of the parameter values are the same as those suggested by the original Gipps car-following model (1981).

Input Parameter	Value
T	5140 Time Steps (514 s)
N	450 vehicles
L	1000 m
meanacc	1.7 m/s ²
stdacc	0.3 m/s ²
rangeacc	0.6 m/s ²
meandecc	-3.4 m/s ²
stddecc	0.4 m/s ²
rangedecc	0.8 m/s ²
meanVd_1	28 m/s
stdVd_1	5 m/s
rangeVd_1	20 m/s
percentVd_1	100 %
meanVd_2	35.55 m/s
stdVd_2	4 m/s
rangeVd_2	52 m/s
percentVd_2	0 %
meansik	0 m
stdrisk	0 m
rangerisk	0 m
meanRT	0.7 s
stdRT	0.3 s
rangeRT	0.4 s
meanLCT	3 s
stdLCT	1 s
rangeLCT	2 s
StartV	28 m/s

Table 4.7: Input Parameters Used in the Model Validation

After running the simulation in both the micro and the macro mode, the time-space diagram of the vehicles with the smallest 50 departure times is shown in Figure 4.5. The corresponding velocity distribution is shown in Figure 4.6.

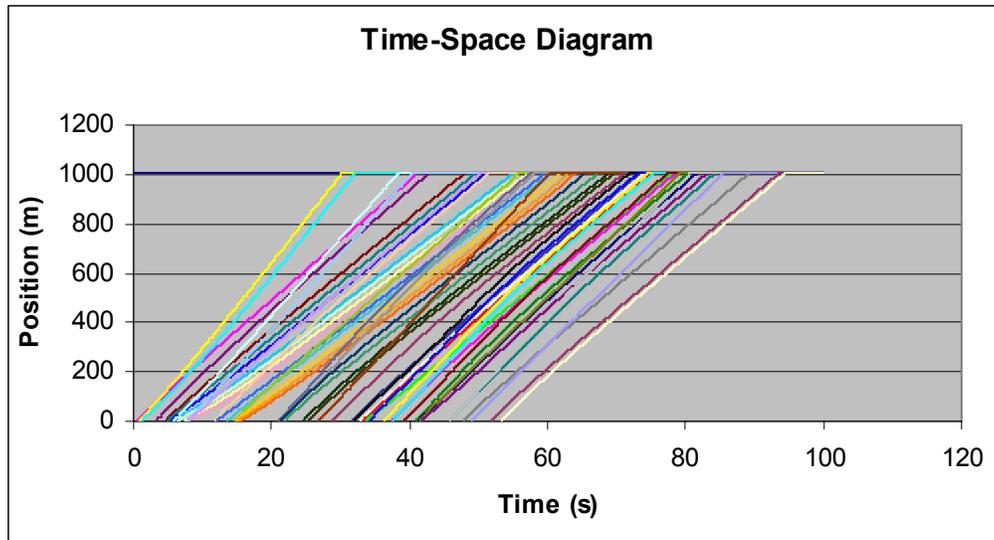


Figure 4.5: Time-Space Diagram of the First 50 Vehicles Entering the Simulation

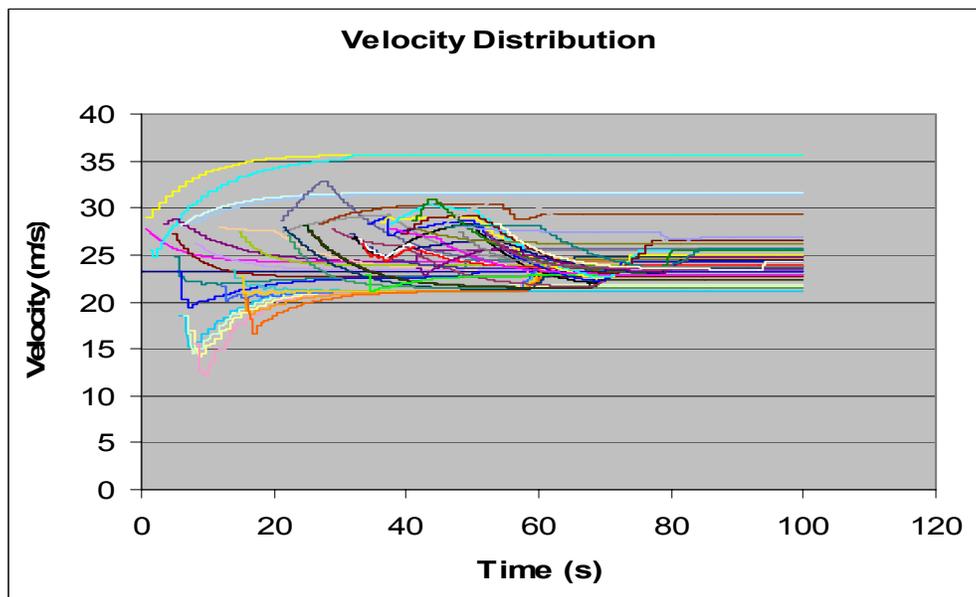


Figure 4.6: Velocity Distribution of the First 50 Vehicles Entering the Simulation

Based on Figure 4.5, the vehicles follow the same traffic pattern observed in Figure 4.3. No major traffic disruption is encountered. Although congested, the traffic is moving smoothly. The average slopes of the trajectory lines are close to

each other. However, the main difference between the two figures is the density of the trajectory lines. This difference is not caused by a logic error implemented in the simulation program. It is caused by the difference in the number of lanes studied. The vehicles observed in Figure 4.3 are traveling on 6 lanes. Those observed in Figure 4.5 are loaded on two lanes only. Since more vehicles can be loaded on a 6-lane highway, the range of departure times in Figure 4.5 is much higher than the one seen in Figure 4.3. For that reason, Figure 4.3 shows a denser time-space diagram. As for the velocity distribution, the range of velocities in Figure 4.4 and 4.6 is mostly between 15 and 35 m/s. Since the first vehicles entering the simulation are loaded on an empty highway section, the velocity distributions at the beginning of the simulation time are smoother than the one shown in Figure 4.4. However, this smoothness is not encountered at the end of the simulation.

As for the aggregate traffic properties, Table 4.7 shows the results obtained from the simulation program versus the data collected.

	Lane Number	Flow (vph)	Space-Mean Speed (m/s)
NGSIM Data	Lane 1	1744	29.97134
	Lane 2	1764	24.95984
	Lane 3	1406	24.5949
	Lane 4	1540	24.75938
	Lane 5	1506	24.5692
	Lane 6	1506	25.02666
	Average	1578	25.62804
Simulation	Lane 1	1527	22.97
	Lane 2	1408	22.79
	Average	1467.5	22.88

Table 4.8: Aggregate Characteristics Obtained by NGSIM Project and the Simulation Program

The main difference in the results is associated with the data observed in lane 1 and lane 2. These lanes show higher flow values than the rest of the lanes. The space mean speed in these lanes is also greater. However, for the rest of the lanes, the results are remarkably close to each other showing that the suggested model can be applied during “normal” driving conditions. The next task is to test the model for its ability to capture panic behavior under extreme conditions. This can be accomplished by conducting the sensitivity analysis discussed in the next two sections.

4.4. Micro-Sensitivity Analysis

Any model attempting to capture panic behavior will be faced with the problem of the limited availability of trajectory data under panic conditions. In general, models with qualitative or speculative validation encounter difficulties in being applied to a wide range of regions and situations. However, since no detailed panic data is available, sensitivity analysis is performed in this and the next sections to test the performance of the modified Gipps model (1981) and the panic characteristics that it can capture. Two kinds of sensitivity are presented. A micro-sensitivity analysis will study the effect of input parameters on the microscopic outputs such as the relative location, headway, velocity and lane changing instances of every vehicle at every time step. On the other hand, the macro-sensitivity considers overall traffic stream behavior in terms of aggregated descriptors such as flow, density and space-mean speed.

In this section, the results obtained under 9 different scenarios are compared with the results of a base-case scenario. The difference in results is then analyzed with respect to the change in the input parameters and their effect. In the base-case scenario, the simulation time is 100 seconds and 50 vehicles are loaded on a 1 kilometer two-lane freeway section. Table 4.9 shows the different values assigned to the driver characteristics in this scenario compared to the other 9 scenarios.

Micro-Sensitivity	Input Parameters Considered										
	Different Scenarios	T (s)	N (veh.)	L (m)	Meanacc (m/s ²)	Meandecc (m/s ²)	MeanVd_1 (m/s)	MeanVd_2 (m/s)	percentVd_1 (%)	Dn (m)	MeanRT (s)
Base-Case	100	50	1000	2	-3.2	13.3	35.5	10	0	1	2
Scenario 2	100	50	1000	2	-3.2	13.3	35.5	10	15	1	2
Scenario 3	100	50	1000	2	-3.2	13.3	35.5	40	15	1	2
Scenario 4	100	50	1000	1.7	-3.2	13.3	35.5	40	15	1	2
Scenario 5	100	50	1000	2	-3.2	13.3	35.5	10	15	1	3
Scenario 6	200	50	2000	2	-3.2	13.3	35.5	10	0	1	2
Scenario 7	200	50	2000	2	-3.2	13.3	35.5	10	15	1	2
Scenario 8	200	50	2000	2	-3.2	13.3	35.5	40	10	1	2
Scenario 9	200	50	2000	2	-3.2	13.3	35.5	40	15	1	2
Scenario 10	200	50	2000	2	-3.2	13.3	35.5	10	15	0.7	2

Table 4.9: Input Parameters in the Scenarios Considered for Micro-Sensitivity

The time-space diagram of the 50 cars is shown in Figure 4.7. Two driving patterns are observed where the two distributions of the desirable speeds can be seen from the two slope values: the slugs and the rabbits. Any intersection between two lines indicates a passing maneuver that is executed onto the adjacent lane.

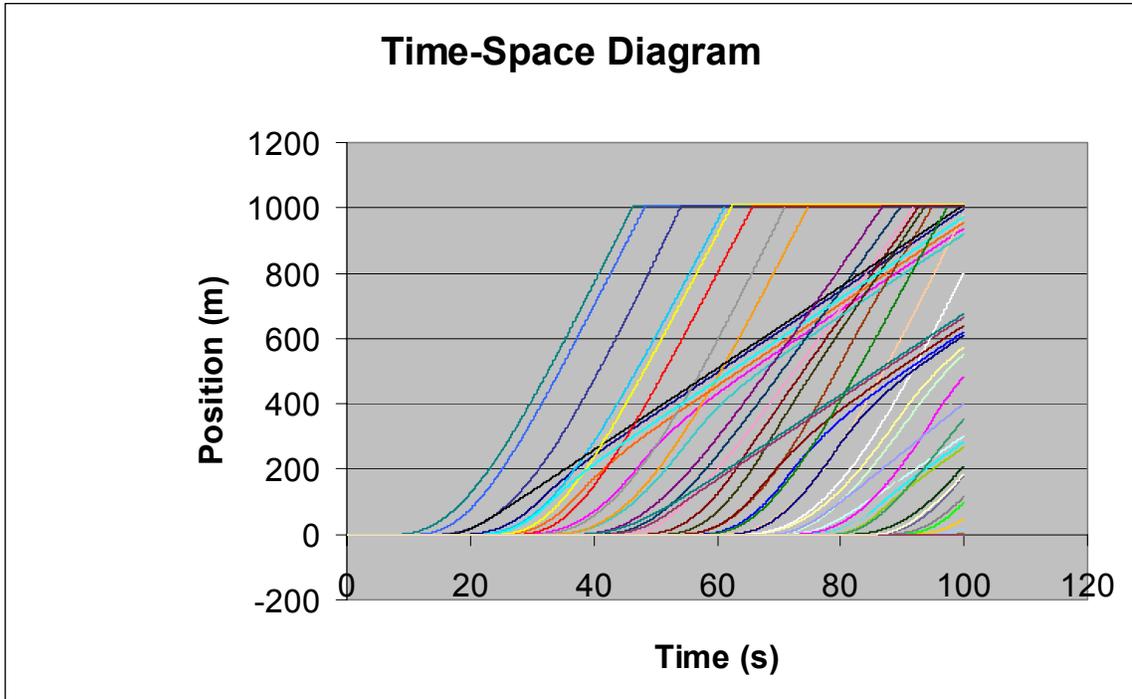


Figure 4.7: Time-Space Diagram of the Base-Case Scenario (Micro-Sensitivity)

For a clearer view, the velocity distribution of the 50 vehicles across time is shown in Figure 4.8. The rabbit velocities vary around 35.5 m/s and the slug velocities vary around 13.3 m/s, as indicated in Table 4.9. All the vehicles start accelerating from a zero initial velocity. The resulting separations are observed in Figure 4.9. These separations can reach a value of 200 meters. The base-case scenario reflects light traffic conditions with low densities. Accordingly, no lane changes need to be performed. With a risk value of zero, no crashes are observed in this scenario.

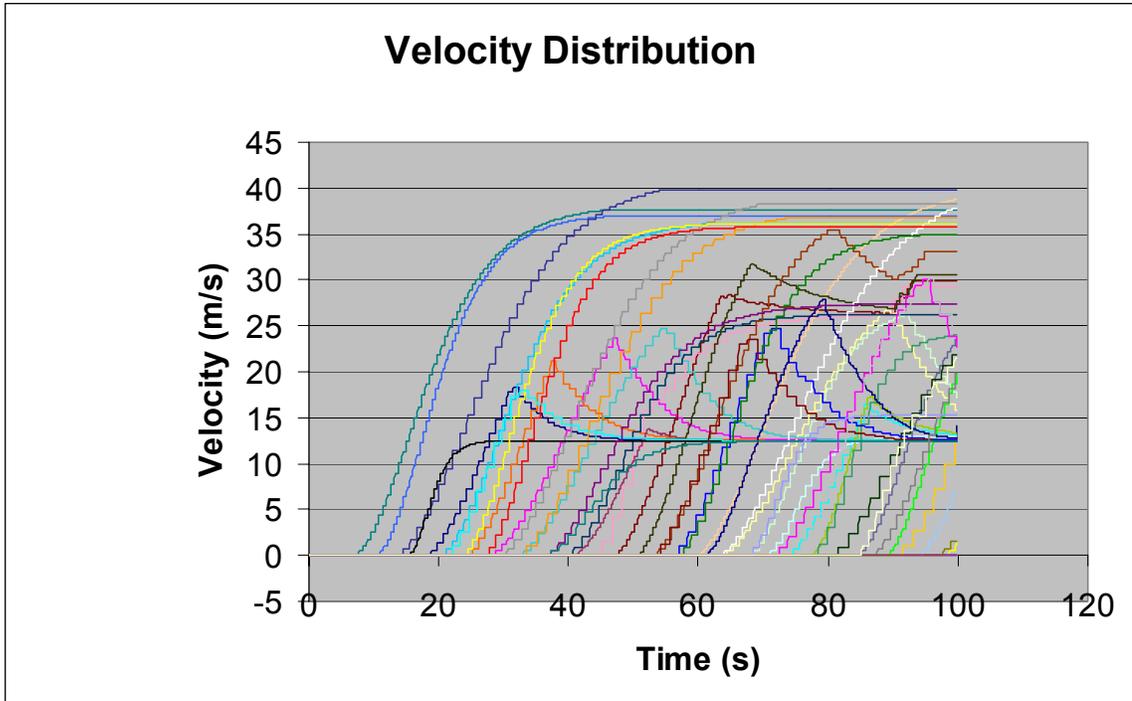


Figure 4.8: Velocity Distribution in the Base-Case Scenario (Micro-Sensitivity)

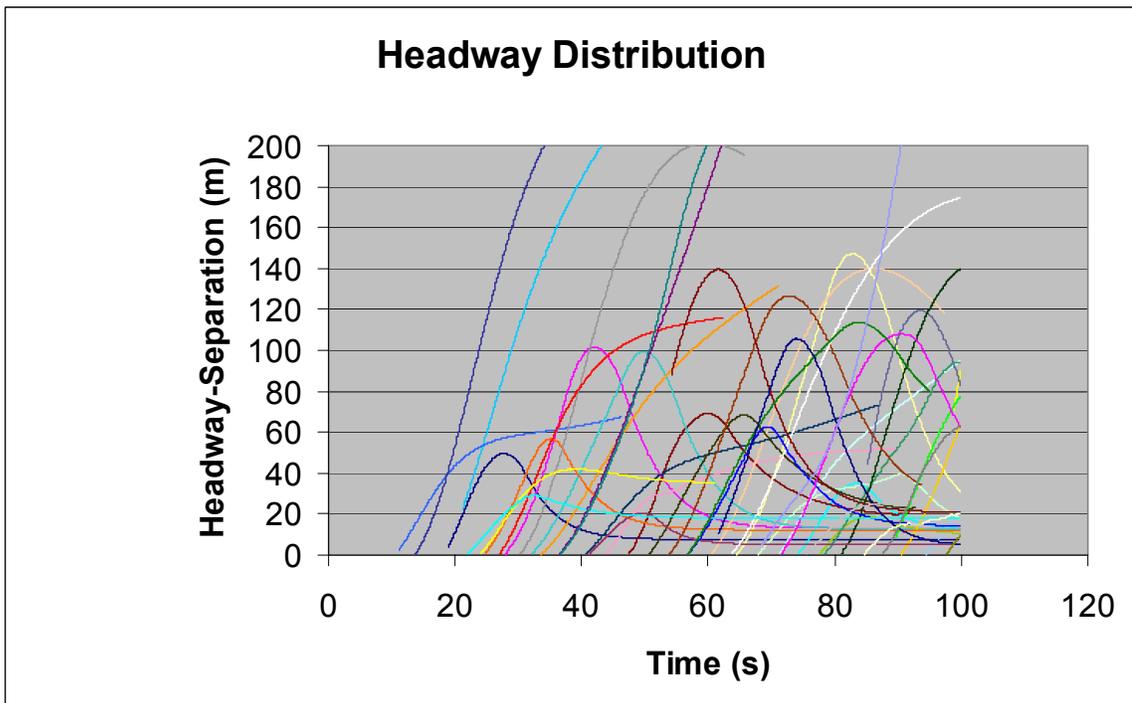


Figure 4.9: Headway Distribution in the Base-Case Scenario (Micro-Sensitivity)

After studying the base-case scenario, all the factors but the “Meanrisk” are kept the same. The risk is increased to 15 meters under Scenario 2. The resulting time space diagram under Scenario 2 is observed in Figure 4.10. Based on the slope, a “slug” vehicle is seen to block some of the other vehicles that departed after it. Their position is kept at around 270 meters; a crash has occurred. As seen in Figure 4.11, there is a slight decrease in the headways compared to the base-case scenario. The increase of the risk value to 15 meters allows drivers to decrease the separation between them and the leading vehicles, ignoring the fact that a rear-end collision may occur. When the separation reaches zero, an accident has occurred. Sometimes, the separation can be less than 5 meters, increasing the necessity for lane changing as indicated in Chapter 3. In this scenario, two lane-changes are observed.

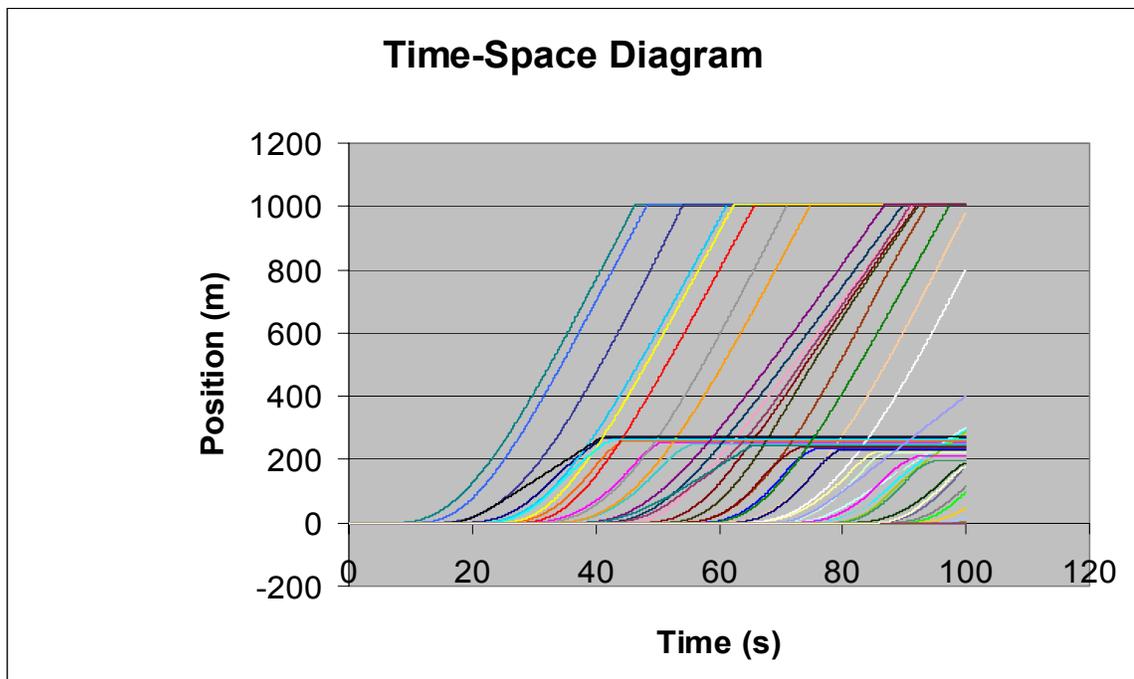


Figure 4.10: Time-Space Diagram of Scenario 2

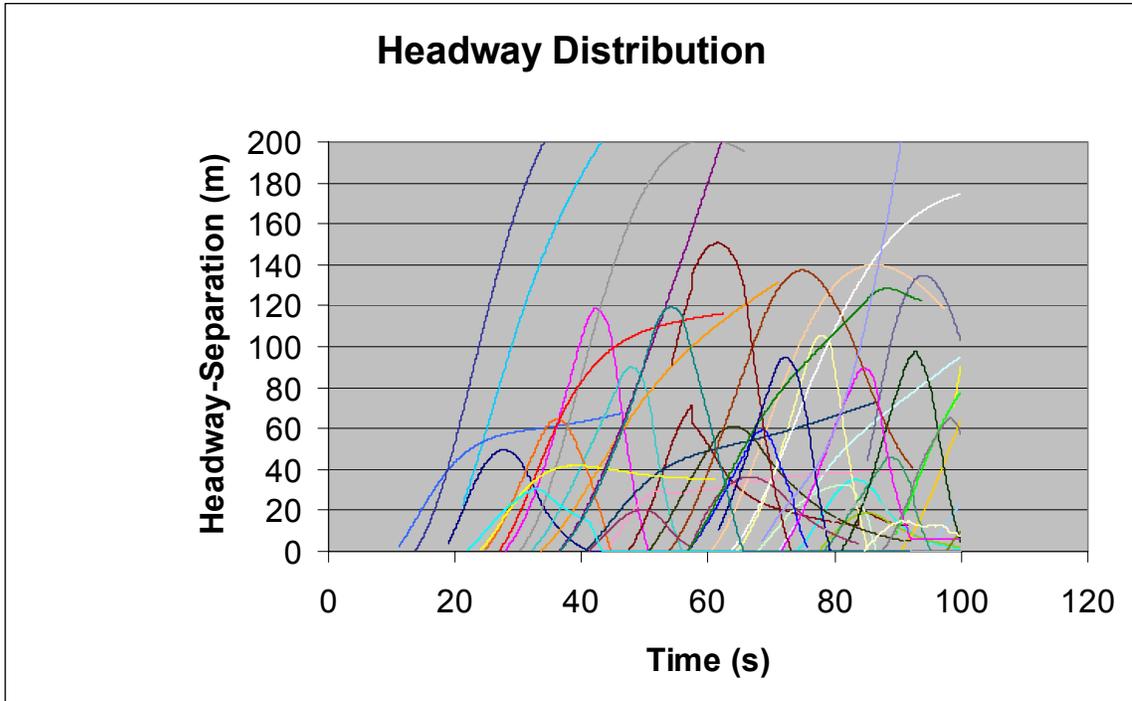


Figure 4.11: Headway Distribution in Scenario 2

The crash distribution along the road length is shown in Figure 4.12. Chain effect crashing is clearly observed in lane 0; one crash leads to a series of crashes since the following vehicles did not have the chance to decelerate in sufficient time to avoid collision.

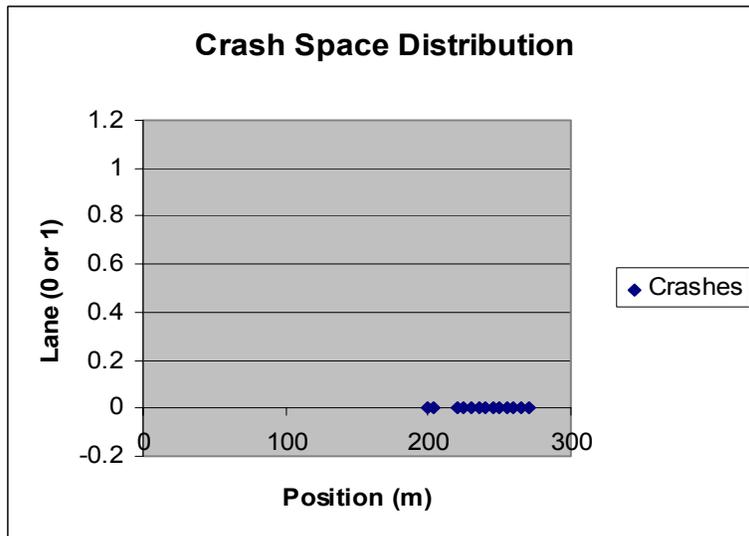


Figure 4.12: Crash Space Distribution in Scenario 2

To study the influence of the “slug” drivers on the traffic, the percent of these drivers is increased to 40%. A value of 15 meters is assigned to “Meanrisk”. The rest of the parameters are kept the same as they were in the base-case scenario. Scenario 3 is then obtained. As shown in Figure 4.13, increasing the number of slow drivers tends to cause more accidents: aggressive drivers traveling at high speed will experience difficulty avoiding a rear-end collision into the slow-moving leaders. The number of accidents not only increases due to the chain-effect mentioned earlier; the accidents are also more evenly distributed along the road length.

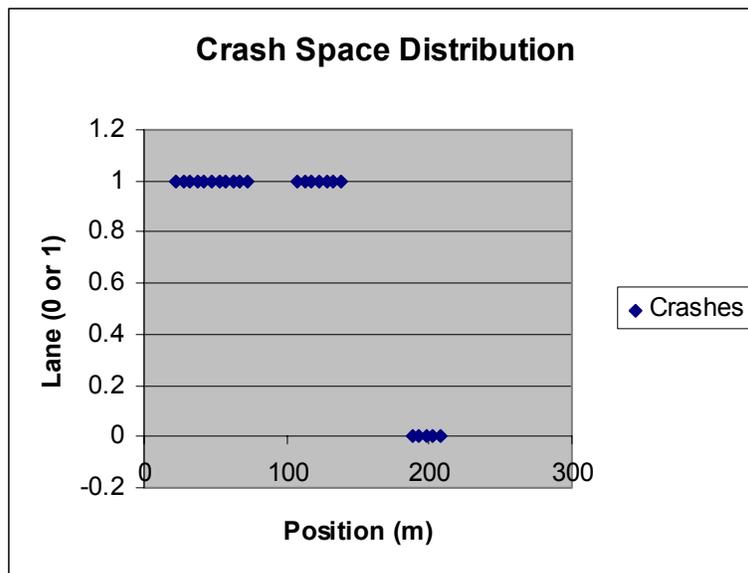


Figure 4.13: Crash Space Distribution in Scenario 3

A higher number of slow drivers on a freeway section causes more tailgating to pressure these drivers to either increase their velocity or move out of the way. This kind of behavior is reflected in the decrease of headways observed in Figure 4.14, when compared to the headways obtained in Scenario 3. As

mentioned earlier, these smaller headways will make drivers more willing to change lanes. Seven lane changes are observed in Figure 4.15 compared to two in Scenario 2.

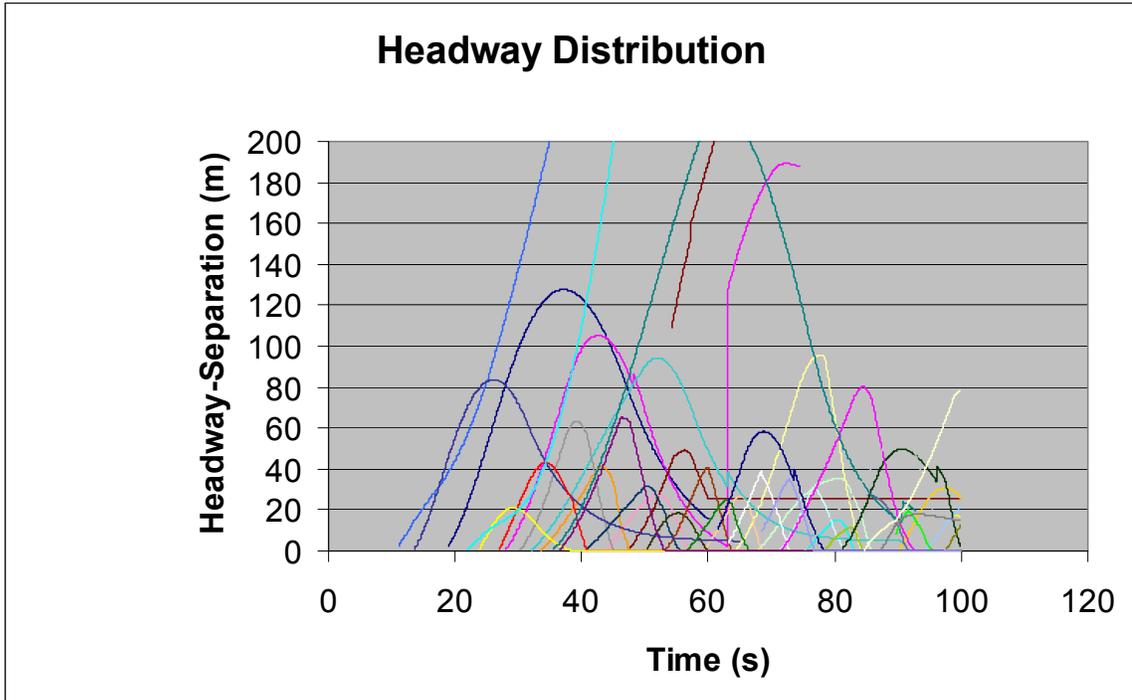


Figure 4.14: Headway Distribution in Scenario 3

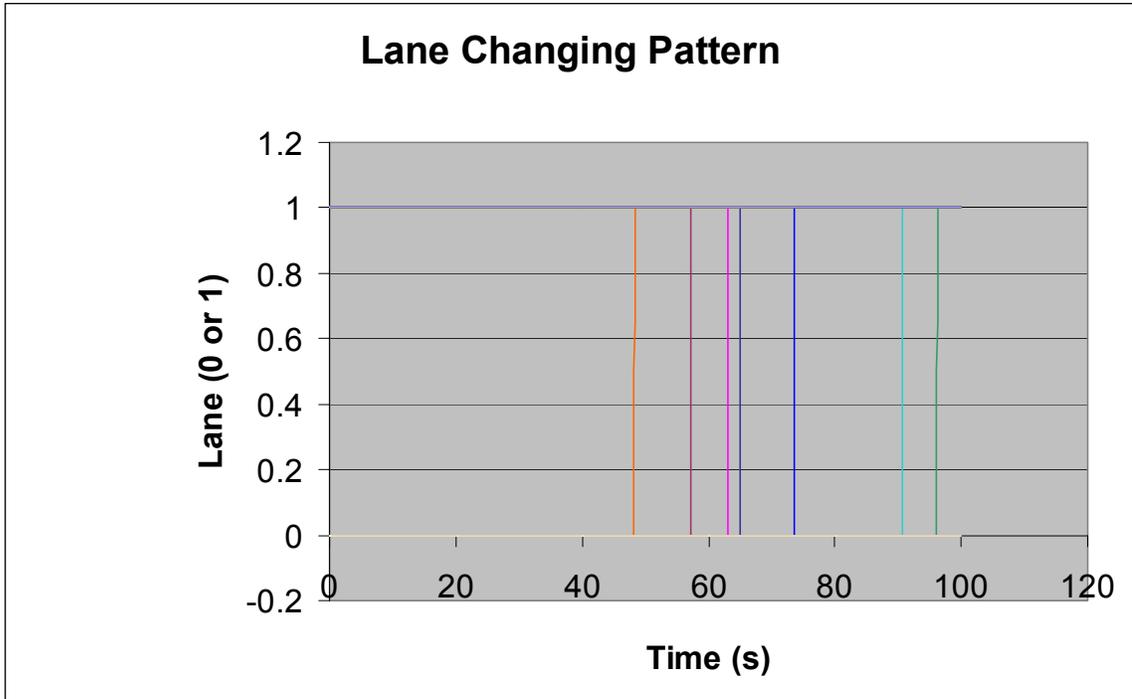


Figure 4.15: Lane Changing Pattern in Scenario 3

When the “Meanacc” is decreased to 1.7 m/s^2 , and keeping the risk factor equal to 15 meters, Scenario 4 is obtained. Based on Figure 4.16, the lower acceleration rates applied by different vehicles will increase the number of possible locations where crashes could occur; after slowing down, drivers will have greater difficulty to accelerate again. The vehicle coming from behind at high speed will have greater difficulty avoiding a rear-end collision. With the increase in the number of accidents distributed along the freeway section, five lane changes are observed.

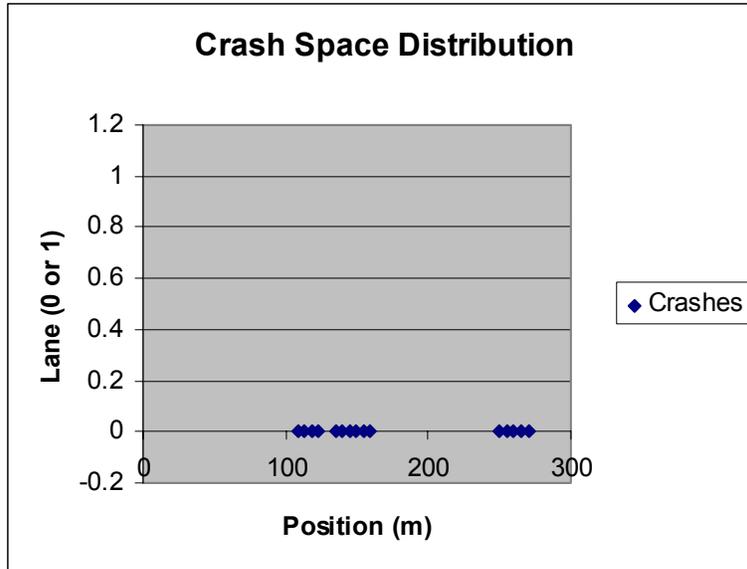


Figure 4.17: Crash Space Distribution in Scenario 5

After considering a simulation time of 100 seconds for the previous five scenarios, the following scenarios differ from the base-case scenario in having a simulation time of 200 seconds on a freeway section length of 2000 meters. Scenario 6 keeps the other drivers' characteristics the same as in the base-case scenario. Since the simulation duration is greater and the departure time is uniformly distributed across this duration, the departure times of different vehicles at the beginning of the simulation will not be so close to each other. The space-headway (separation) is then expected to increase. This increase is reflected in the increase of the vertical distance between lines presented in the time-space diagram of Figure 4.18. Moreover, this figure shows that some of the “rabbit” vehicles depart after some slug vehicles and therefore get blocked later on behind them.

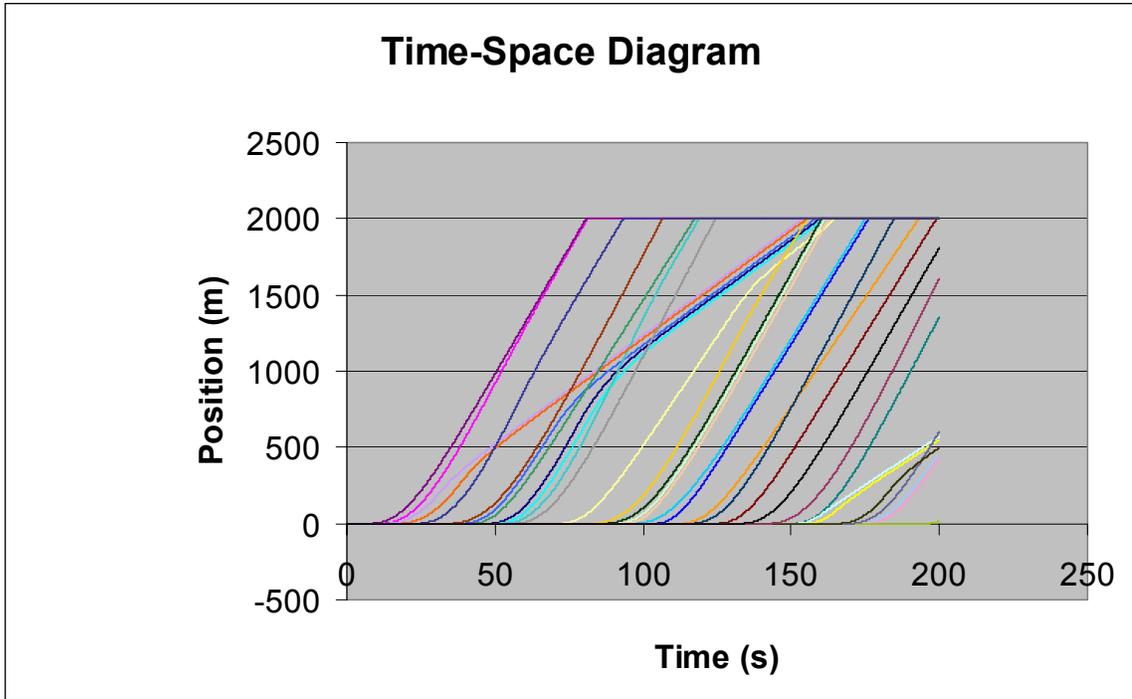


Figure 4.18: Time-Space Diagram of Scenario 6

With a more spacious road section and less congestion due to the wider range of departure times, vehicles have greater freedom to reach their desired velocity in a smoother manner. The increase of the road length has no direct effect on the driver's behavior. It may just allow space-headways to reach higher values near the boundary, as observed in Figure 4.19. There are no accidents observed in this scenario due to a zero risk factor. There is no need for lane changing either.

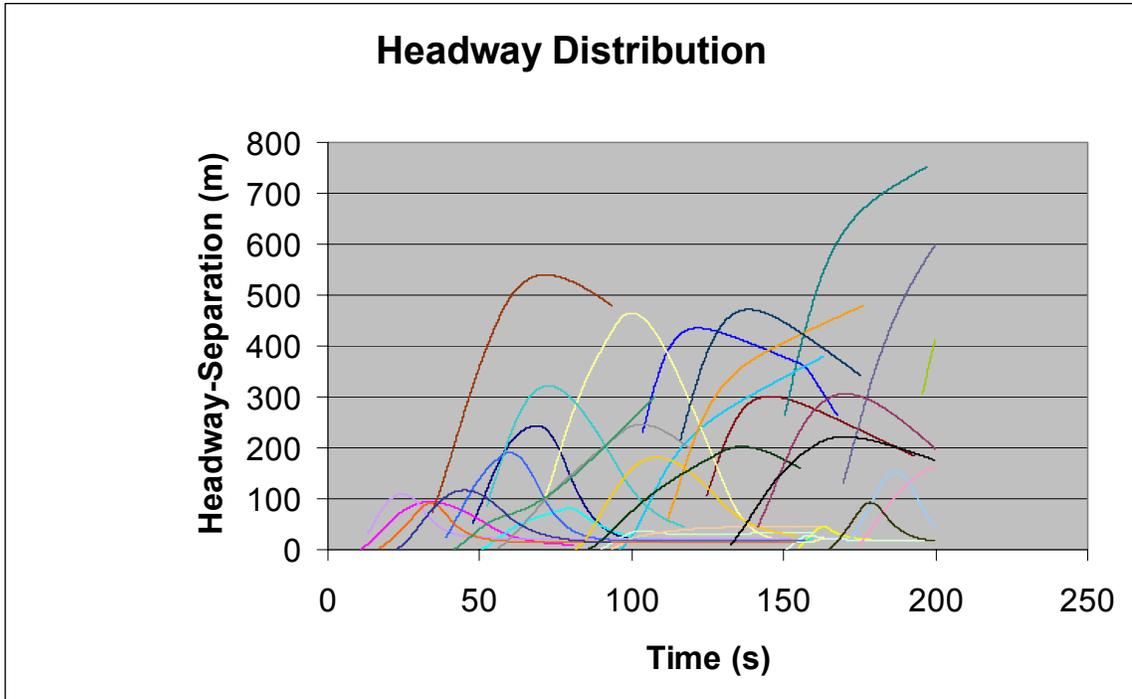


Figure 4.19: Headway Distribution in Scenario 6

Scenario 7 is defined by only changing the risk factor to 15 meters, while keeping the other parameters at the same level as in Scenario 6. As shown in Figure 4.20, a slight decrease in headways will cause six lane changes instead of zero lane changes in Scenario 6. This increase in risk taking creates some accidents. However, these accidents are not as numerous as observed in scenario 2 with the same risk factor but with a simulation time of 100 seconds and a freeway section of 100 meters; it is less likely to encounter accidents over a more spacious road with larger headways for the same risk value. Figure 4.21 illustrates this phenomenon.

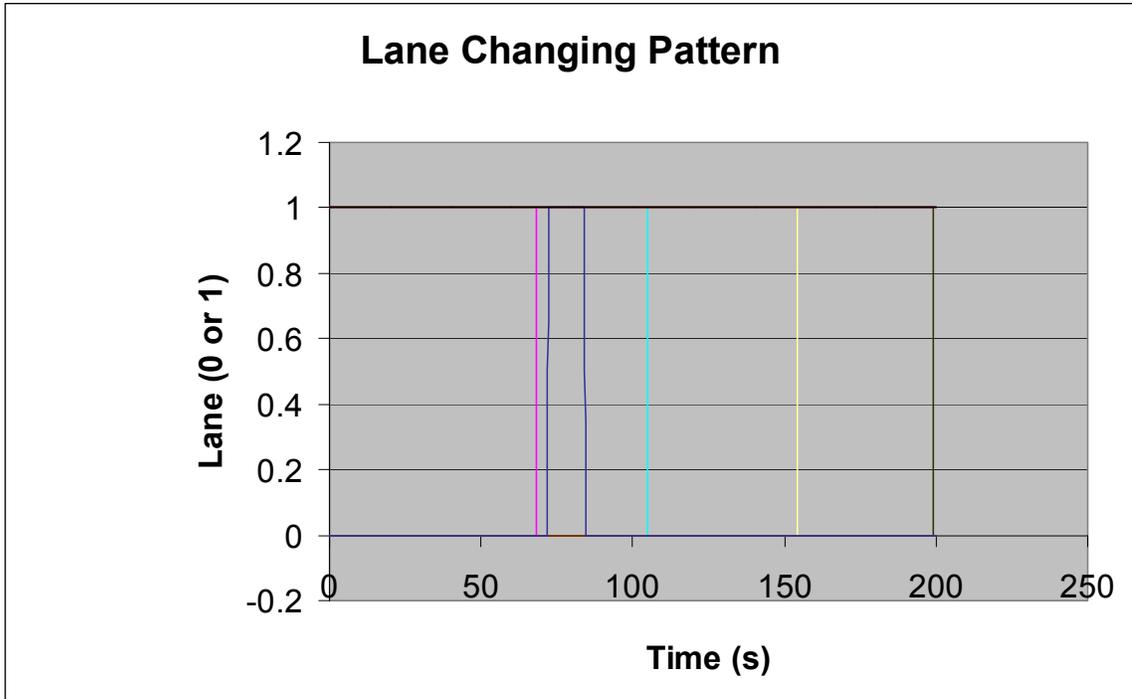


Figure 4.20: Lane Changing Pattern in Scenario 7

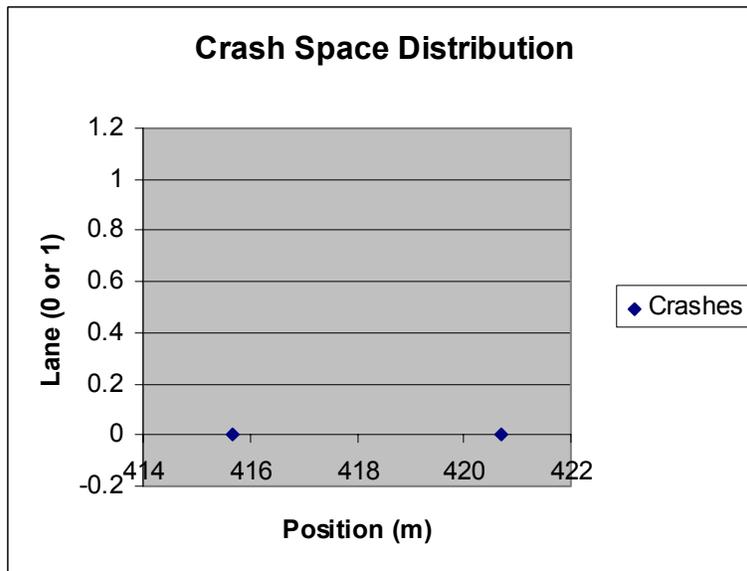


Figure 4.21: Crash Space Distribution in Scenario 7

Relative to Scenario 7, Scenario 8 consists of decreasing the risk factor from 15 to 10 meters, and increasing the percentage of “slug” drivers to 40%. Even with lower risk value, the larger proportion of “slugs” in the population

increases the number of accidents in an evenly distributed manner. The accidents shown in Figure 4.22 are positively correlated with the general “push down” of space headways shown in Figure 4.24. This will in turn increase the frequency of lane changing maneuvers (Figure 4.23).

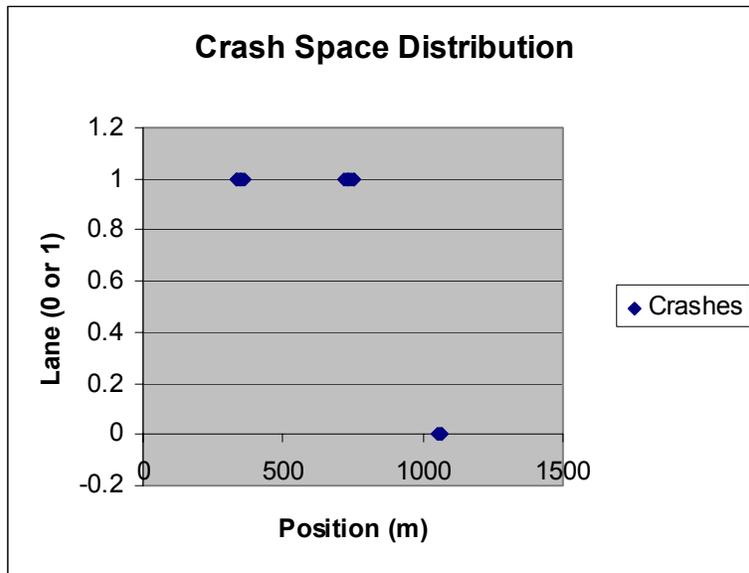


Figure 4.22: Crash Space Distribution in Scenario 8

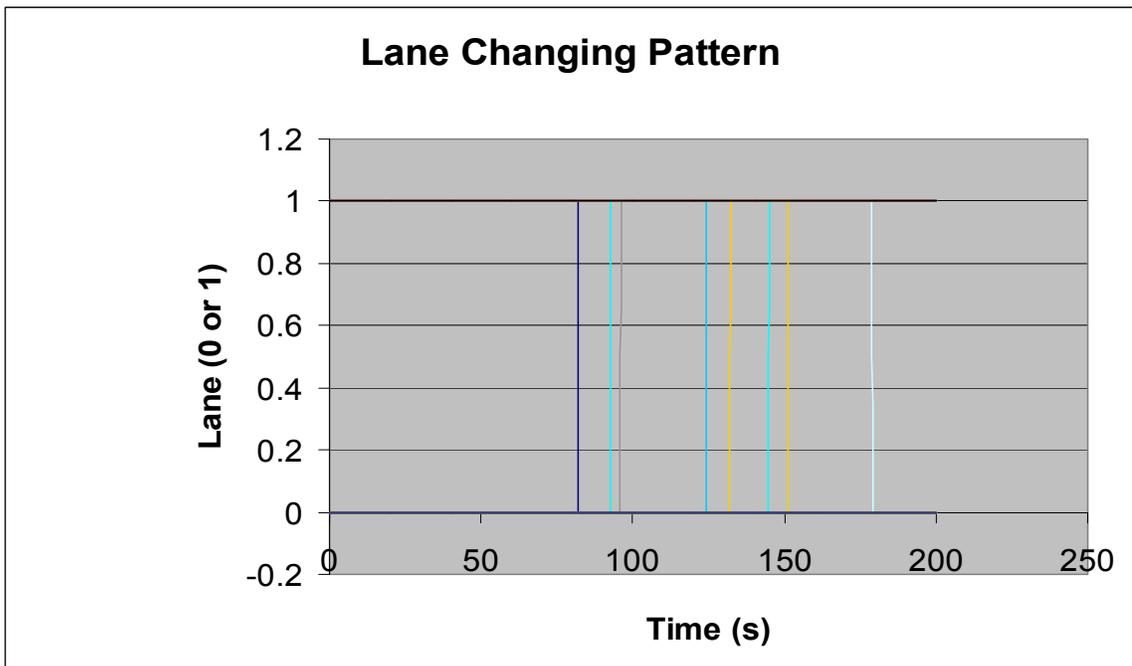


Figure 4.23: Lane Changing Pattern in Scenario 8

As already explained in conjunction with Scenario 3, the considerable decrease in the headways captures the tailgating performed by the aggressive drivers of the slow vehicles blocking the way.

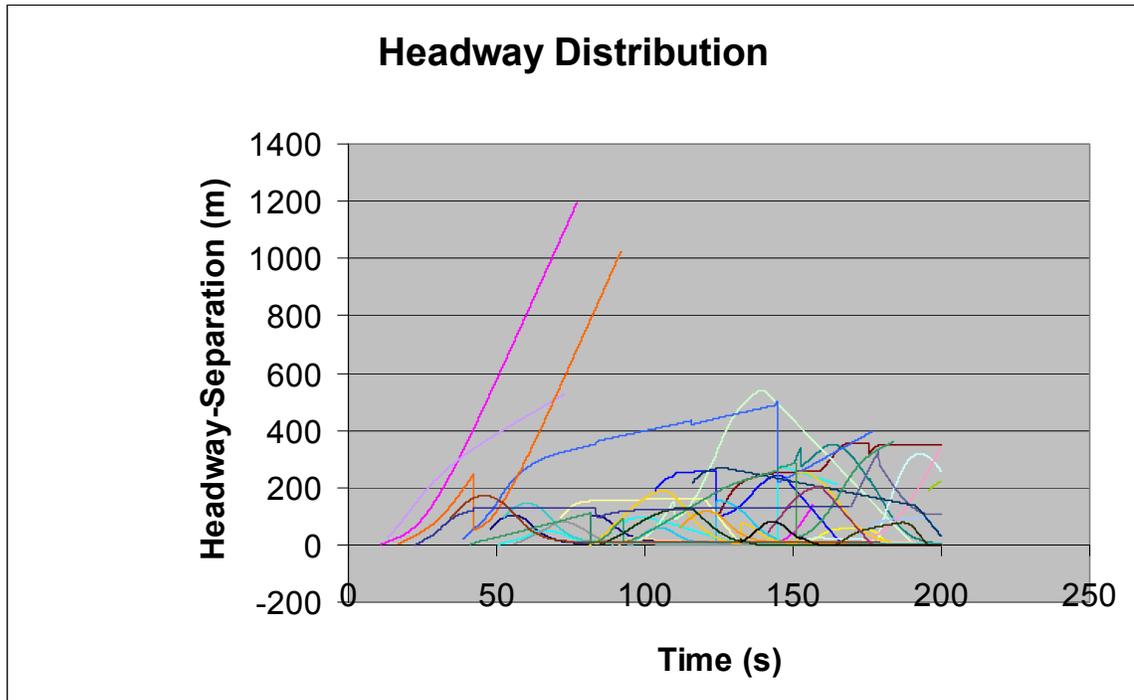


Figure 4.24: Headway Distribution in Scenario 8

Scenario 9 differs from Scenario 8 in that the risk factor is increased from 10 back to 15 meters. The higher risk factor will further push down the headways between vehicles, exacerbating the tailgating phenomenon (Figure 4.25). Moreover, Figure 4.26 shows that the chain-type accidents increase in frequency. However, the accident locations are similar to those obtained in the previous scenario.

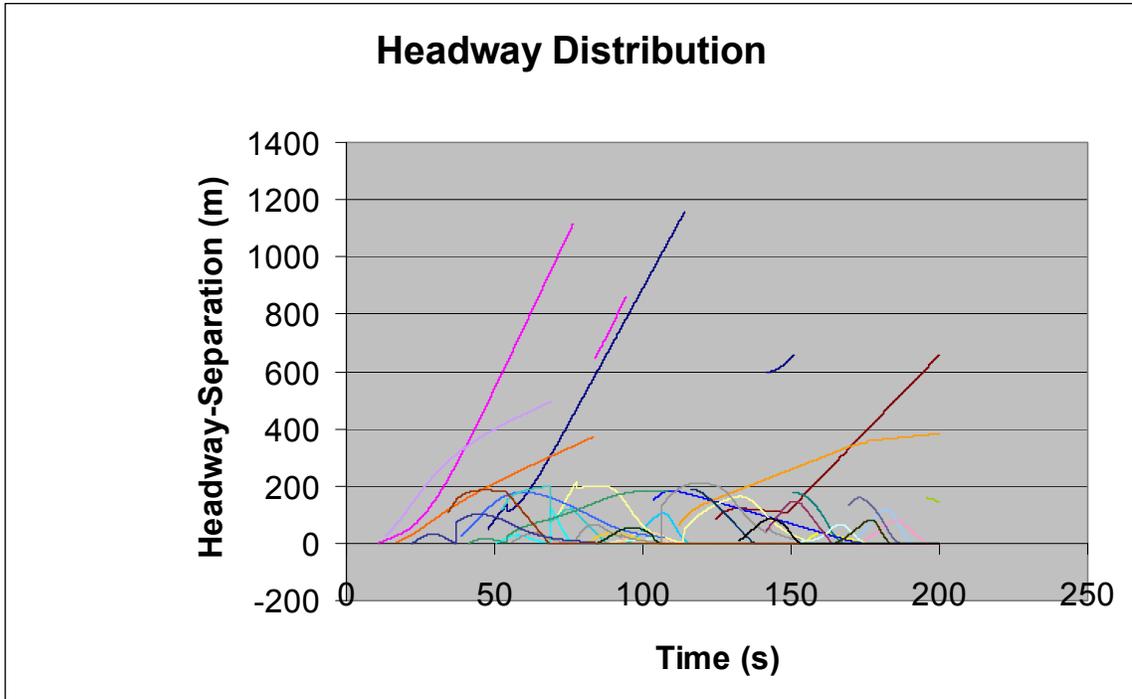


Figure 4.25: Headway Distribution in Scenario 9

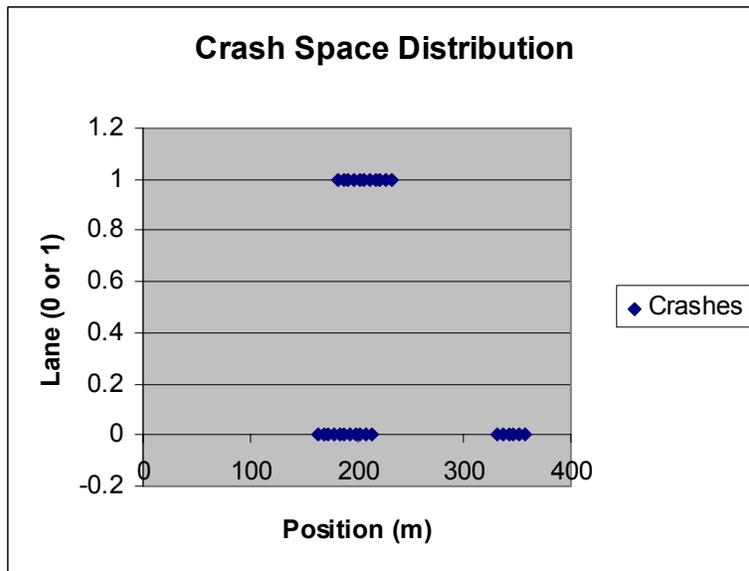


Figure 4.26: Crash Space Distribution in Scenario 9

Scenario 10 aims to study the effect of the driver's reaction time on the other microscopic output results. The reaction time (MeanRT) is decreased to 0.7 seconds and the other parameters are kept the same as in Scenario 7. The

lower reaction time reflects heightened alertness on the part of the drivers, which produces a slight increase in the space-headways and results in a lower number of accident locations. Figures 4.27 and 4.28 illustrate this finding.

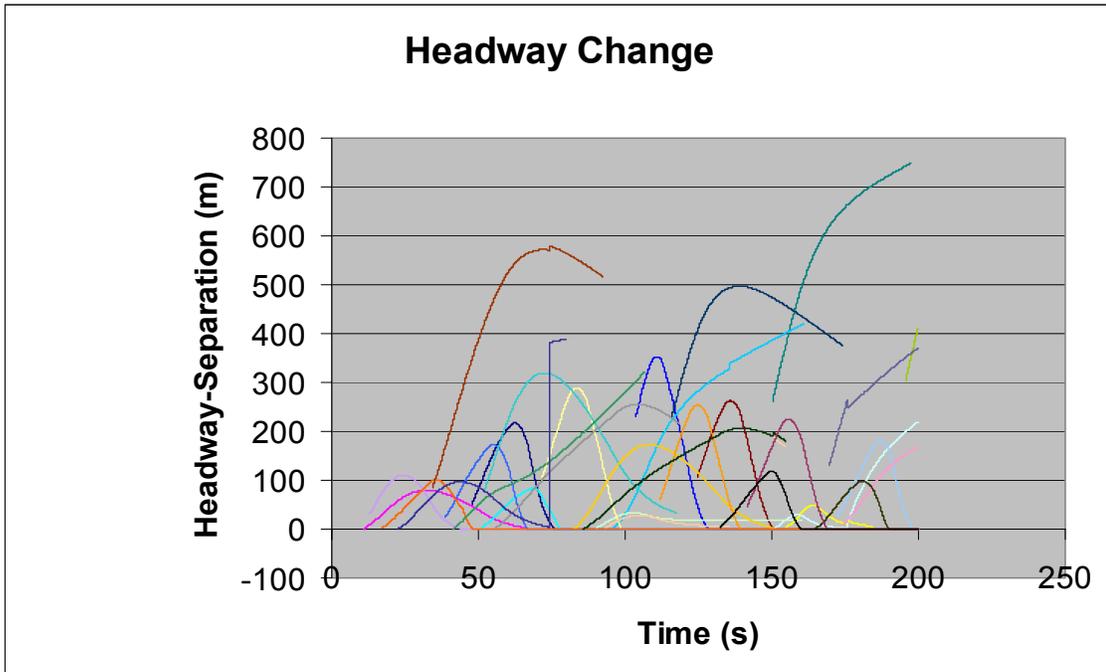


Figure 4.27: Headway Distribution in Scenario 10

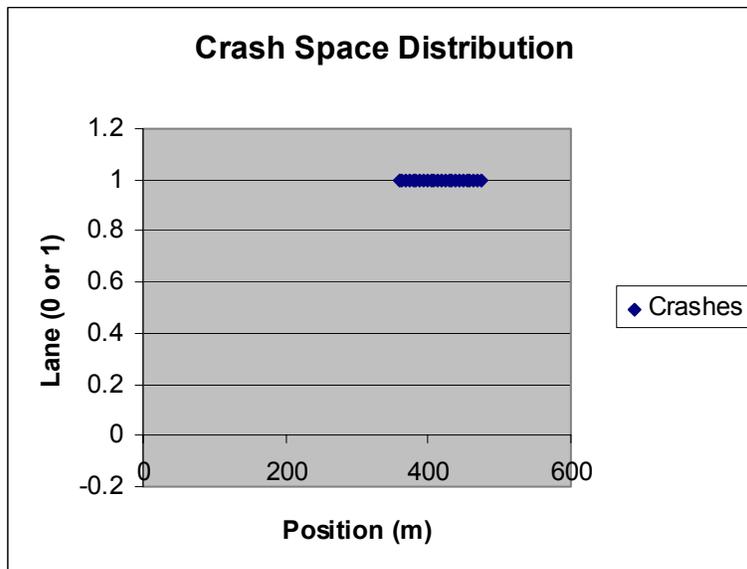


Figure 4.28: Crash Space Distribution in Scenario 10

Other runs were conducted for additional testing purposes. The principal finding from those pertains to the effect of the deceleration rates (Meandecc). Lower allowable deceleration rates increase the frequency of chain-type accidents; once an accident occurs, the following drivers will not be able to slow down in sufficient time to avoid the crash.

The micro-simulation sensitivity analysis has generally confirmed that the modified Gipps model (1981) produces the intended phenomena, and provides a reasonable model representation of several important characteristics of panic behavior under extreme conditions. For a complete assessment, the macroscopic output results are next investigated with respect to the different input parameters discussed earlier.

4.5. Macro-Sensitivity Analysis

This section shows the effect of selected input parameters on the aggregate traffic characteristics such as flow, density and space mean speed. The same procedure adopted in Section 4.4 is adopted here: the base-case scenario considers a total number of 200 vehicles loaded on a 3 km highway section for 514 seconds. These values assume normal traffic conditions with a unimodal velocity distribution and zero risk factor. Four other scenarios are studied in the macro-sensitivity analysis where the input parameters changes are shown in Table 4.10.

Macro-Sensitivity	Input Parameters Considered										
Different Scenarios	T (s)	N (veh.)	L (m)	Meanacc (m/s ²)	Meandecc (m/s ²)	MeanVd_1 (m/s)	MeanVd_2 (m/s)	percentVd_1 (%)	Dn (m)	MeanRT (s)	MeanLCT (s)
Base-Case	514	200	3000	1.7	-3.2	27	27	0	0	0.7	3
Scenario 11	514	200	3000	1.7	-3.2	27	27	0	5	0.7	3
Scenario 12	514	200	3000	1.7	-3.2	27	27	0	10	0.7	3
Scenario 13	514	200	3000	1.7	-3.2	13.3	35.5	40	5	0.7	3
Scenario 14	514	200	3000	1.7	-3.2	13.3	35.5	40	5	1	3

Table 4.10: Input Parameters in the Scenarios Considered for Macro-Sensitivity

With zero accidents observed in the base-case scenario, the flows and the space-mean speeds on the different lanes are shown in Tables 4.11 and 4.12 respectively.

Flow (vph)	Lane		Average
Km Section	Lane 1	Lane 2	
Km 1	630.36	644.36	637.36
Km 2	602.34	623.34	612.84
Km 3	539.3	595.34	567.32

Table 4.11: Flows Observed in Base- Case Scenario (Macro-Sensitivity)

Space Mean Speed (m/s)	Lane		Average
Km Section	Lane 1	Lane 2	
Km 1	25.68	25.12	25.4
Km 2	25.03	24.31	24.67
Km 3	24.31	23.99	24.15

Table 4.12: Space-Mean Speeds Observed in Base-Case Scenario (Macro-Sensitivity)

The flow values observed in Table 4.11 suggests that low-density traffic is encountered in this scenario. This traffic is moving smoothly at an average velocity of 24.74 m/s. The variation of the density in lane 1 and lane 2 over time

is presented in Figures 4.29 and 4.30. In each of the two figures, it can be seen how the “density change” is propagating from one Km section to another. The maximum density values in this Scenario are 17 vehicles per Km per lane on lane 1 and 14 vehicles per Km per lane on Lane 2.

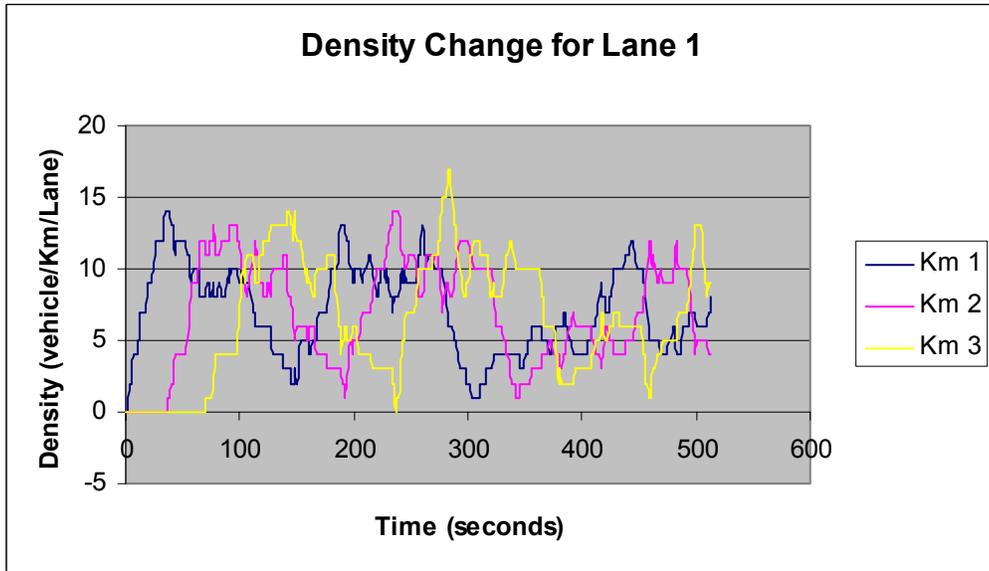


Figure 4.29: Density Change on Lane 1 during Base-Case Scenario (Macro-Sensitivity)

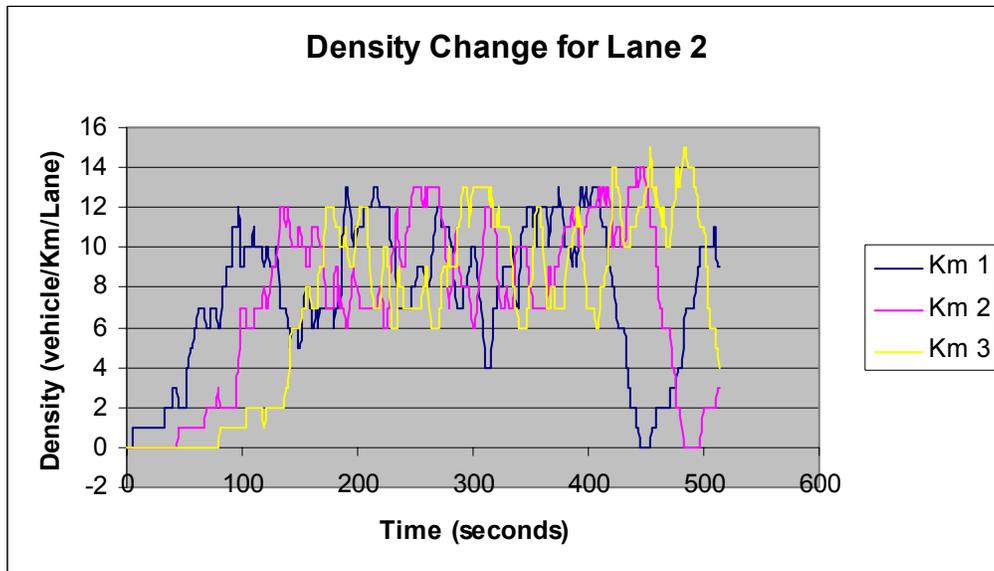


Figure 4.30: Density Change on Lane 2 during Base-Case Scenario (Macro-Sensitivity)

Scenario 11 is obtained by increasing the risk factor to 5 meters and keeping the other parameters the same as in the above base-case scenario. The accident distribution is shown in the Figure 4.31.

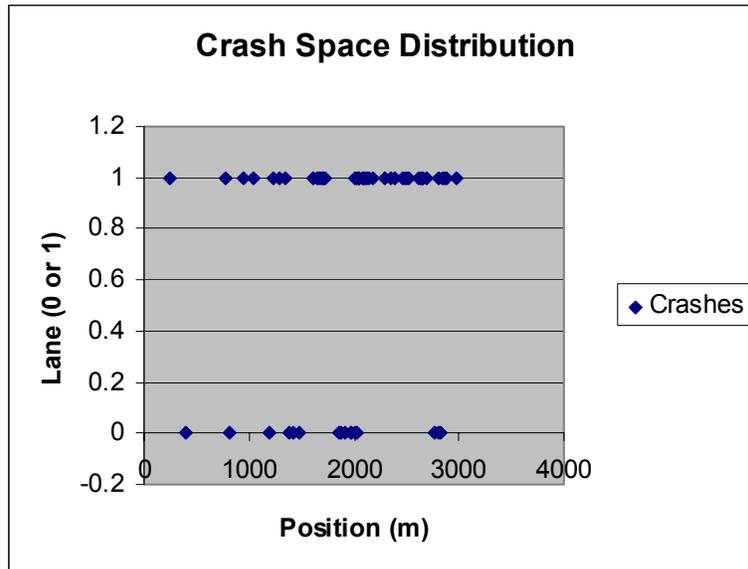


Figure 4.31: Crash Space Distribution in Scenario 11

Due to these accidents, the mobility of traffic is slowed down. The flow values decrease systematically on the different lanes. This decrease can be observed by comparing Table 4.11 to Table 4.13.

Flow (vph) Km Section	Lane		Average
	Lane 1	Lane 2	
Km 1	630.36	630.36	630.36
Km 2	602.34	532.3	567.32
Km 3	483.26	427.24	455.25

Table 4.13: Flows Observed in Scenario 11

Another phenomenon observed is the variation of these flows as one travels downstream along the highway length. Due to the increase in the number

of vehicles involved in accidents in the previous road segments, the flows decrease until reaching a minimum value in the last kilometer.

Scenario 12 is obtained by further increasing the risk value to 10 meters. The other parameters are left unchanged. This change leads to an increase in the number accidents and thus, a further decrease in the flow values. Table 4.14 and Figure 4.32 illustrate the results.

Flow (vph)	Lane		Average
	Lane 1	Lane 2	
Km 1	616.34	623.34	619.84
Km 2	532.3	497.28	514.79
Km 3	413.22	364.2	388.71

Table 4.14: Flows Observed in Scenario 12

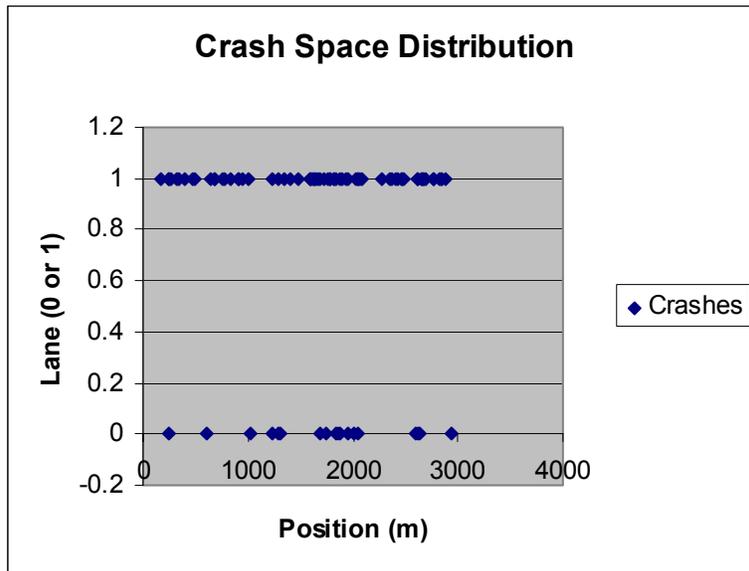


Figure 4.32: Crash Space Distribution in Scenario 12

As shown in the micro-sensitivity analysis, the increase in the number of “slug” drivers has a considerable influence on the microscopic output results. To study this influence on the macroscopic aggregate traffic characteristics, the desired velocity distribution with a mean of 17 m/s is replaced by a 40-60%

probability mixture of two desired velocity distributions with respective means 13.3 m/s (slugs, 40%) and 35.5 m/s (rabbits, 60%). The risk factor is 5 meters and the rest of the input parameters are kept the same as in Table 4.10. These parameter values define Scenario 13. Even with a lower risk factor than in Scenario 12, the increase in the number of slug drivers causes a considerable increase in the number of accidents (Figure 4.33). The flows are even lower than those observed with a risk factor of 10 meters. The decrease in flows can be observed by comparing Table 4.15 with Table 4.14.

Flow (vph)	Lane		Average
Km Section	Lane 1	Lane 2	
Km 1	504.28	511.28	507.78
Km 2	315.18	336.18	325.68
Km 3	231.12	280.16	255.64

Table 4.15: Flows Observed in Scenario 13

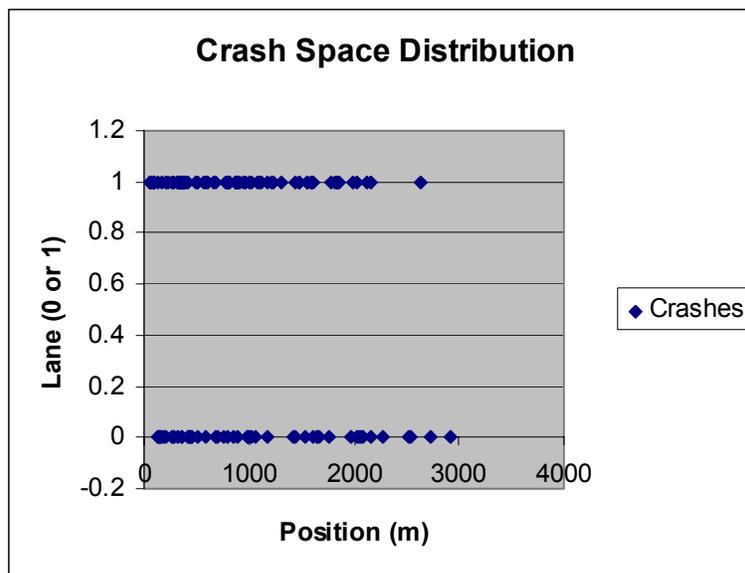


Figure 4.33: Crash Space Distribution in Scenario 13

Due to the increase in the number of “chain-effect” accidents at the beginning of the highway length, the space-mean speeds in the first “1 Km

sections” are slightly less than in the last ones (Table 4.16). Once a vehicle overcomes the accidents concentrated at the beginning, it will be able to travel more freely. This situation may not apply in real life applications, especially that the number of vehicles in these situations is not limited as it is in this scenario. Moreover, the “chain-effect” mentioned above increases the density values in the sections where the accidents occur.

Space Mean Speed (m/s)	Lane		Average	
	Km Section	Lane 1		Lane 2
	Km 1	16.33	16.29	16.31
	Km 2	16.94	18.27	17.605
	Km 3	16.48	35.28	25.88

Table 4.16: Space-Mean Speeds Observed in Scenario 13

The final conclusion from this scenario is related to the traffic disruption observed with the increase of the number of slug drivers. As shown in Figures 4.34 and 4.35, the change of the densities over time is less smooth than was observed under normal conditions (Figures 4.29 and 4.30). The drivers travel in discontinuous platoons following the “slugs” who are blocking the road.

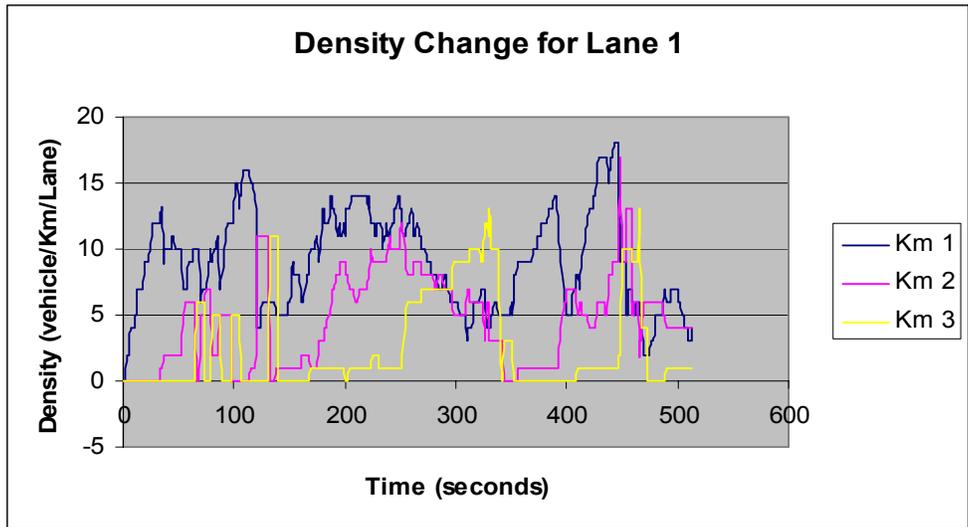


Figure 4.34: Density Change on Lane 1 during Scenario 13

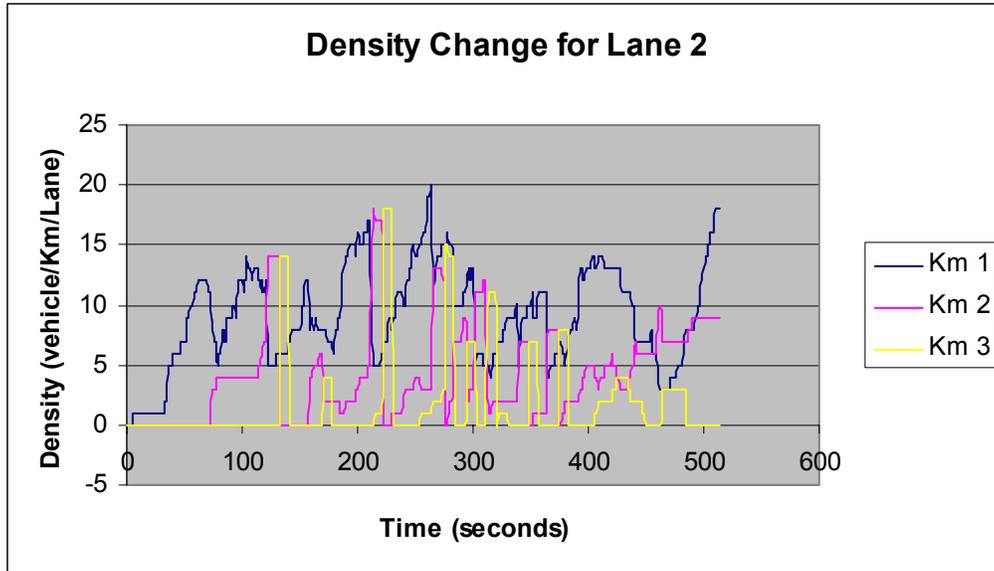


Figure 4.35: Density Change on Lane 2 during Scenario 13

The final scenario discussed in this chapter is Scenario 14, which consists of keeping all the input parameters of Scenario 13 and increasing the reaction time to 1 second. This increase in the reaction time does not have a significant effect on the number of accidents, but rather on the way they are distributed. Figure 4.36 shows that these accidents are more evenly distributed over the entire highway section, resulting in a decrease of the space-mean speeds throughout, compared to a decrease in the first sections only in Scenario 13. This can be illustrated by comparing Table 4.17 to Table 4.16.

Space Mean Speed (m/s)	Lane		Average
	Km Section	Lane 1	
Km 1	14.52	13.63	14.075
Km 2	14.5	14.65	14.575
Km 3	19.62	17.15	18.385

Table 4.17: Space-Mean Speeds Observed in Scenario 14

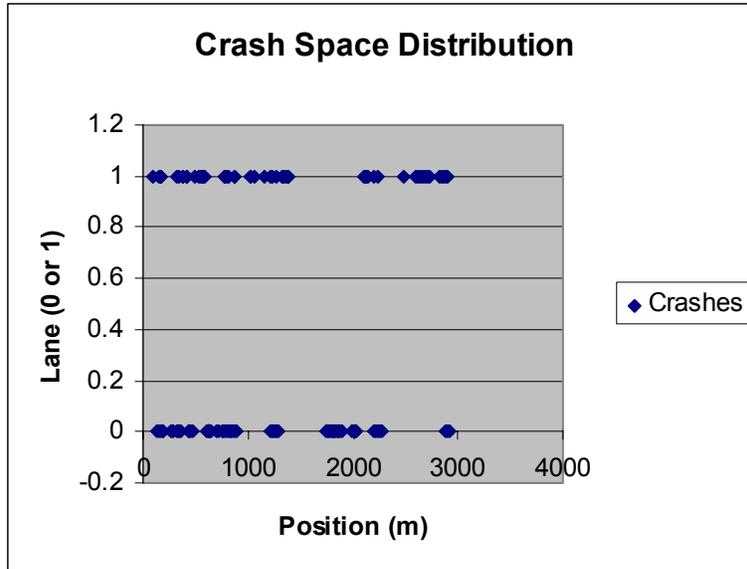


Figure 4.36: Crash Space Distribution in Scenario 14

Even though their influence is investigated in the micro-sensitivity analysis, other factors, such as the lane changing time, the acceleration rates, and the deceleration rates, appear to have minimal effect on the aggregate traffic characteristics. The risk factor, the velocity distribution and the reaction times are the dominant input parameters that need to be addressed in the macroscopic sensitivity analysis.

4.6. Summary

The modified Gipps model proposed in Chapter 3 is implemented in a simulation program coded in the C++ language. Due to the unavailability of traffic data under panic conditions, this model was partially validated using “normal” data collected under the US Federal Highway Administration’s Next Generation Simulation (NGSIM) Project managed by Cambridge Systematics,

Inc. (2004). Testing the model using a micro-sensitivity analysis, the model could capture the following panic behavioral characteristics:

1- Tailgating and decrease of headways

2- Increase of velocities for aggressive drivers

6- Increase in number of accidents

The emergency breaking and the higher acceleration rates are suggested to be modeled directly by decreasing the “meandec” value and increasing the “meandec” value respectively. Moreover, sudden lane changing is captured by the decrease of the lane changing time (LCT) factor. The increase of the risk factor combined with a higher percentage of “slug drivers” is the major source of accidents. The majority of these accidents are “chain-type” accidents that mostly occur when aggressive drivers are not able to apply the necessary deceleration rate to avoid a rear-end collision with a leading slug driver. On the other hand, the increase in reaction time is a reflection of the decrease of drivers’ alertness under extreme conditions due to the increasing number of surrounding moving stimuli. This lack of alertness is a direct cause of distributing the accidents more uniformly along the road length instead of being concentrated at a particular location due to the “chain effect”.

On the other hand, the only input parameters that have a significant influence on the aggregate driver characteristics are the risk factor, the velocity distributions and the reaction time. The increase in the number of slug drivers causes a non-smooth change of density over time. The sudden increase or decrease of densities is due to the fact that drivers travel in discontinuous platoons

following a given “slug driver”. This effect, combined with an increasing risk factor, decreases the flows and the space-mean speeds on the first sections of the highway, where most of the accidents are concentrated. However, the increase of the reaction time distributes the accidents more uniformly and thus, causes a general decrease of the flows and the space-mean speeds. The only significant increase of the densities is encountered when chain-type accidents occupy a considerable length of a highway section.

CHAPTER 5: SUMMARY AND CONCLUSIONS

5.1. Introduction

This chapter presents a summary of the major findings of this study and addresses future research needs in the area of modeling driver behavior under extreme conditions. The first section provides the summary of key findings and a discussion of their implications. In addition, improvements to the model developed in this study are mentioned. The second section suggests some directions for further investigation in modeling panic behavior under extreme conditions.

5.2. Summary

This study addresses the influence of extreme conditions on drivers' behavior, and presents an approach for representing this behavior in the context of an operational traffic simulation capability. Since panic is a key factor in life-threatening extreme conditions, a micro-simulation model that aims to represent driver behavior under panic conditions is developed. After studying several existing traffic models, the main purpose for adopting a microscopic approach was to relate the effect of behavioral changes at the individual driver level to the resulting aggregate traffic characteristics. The individual behavioral changes proposed were derived primarily through inference and synthesis of the body of psychological studies conducted on panic.

Gipps' (1981) car-following model was modified and implemented in computer code. The model is able to address the following driving characteristics:

1- Tailgating and decrease of headways

2- Increase of velocities for aggressive drivers

3- Higher acceleration rates with non-smooth change of velocities

4- Higher deceleration rates and emergency braking

5- Higher Velocity Variance due to the presence of aggressive drivers (rabbits) and slow drivers (slugs) who are either lost or still rationalizing their decisions

6- Increase in the number of accidents.

Several major conclusions and insights can be drawn from the various runs conducted under different scenarios. First, most of the accidents observed are chain-type accidents, caused by sudden stops or crashes in which leading vehicles are involved. It can be also concluded that the increase of reaction time under panic situations is one of reasons for the increase in the number of crashes observed. As for the macroscopic aggregate traffic characteristics, the main three influence factors consist of the following: (1) a risk factor reflecting spatial tolerance for accidents, (2) the percent of slow drivers encountered, and (3) the reaction time distribution across drivers. As the risk factor and the percent of slow drivers increase, the number of accidents increases as well. These accidents are better distributed over the road length due to the lower alertness of the drivers reflected by the increase of the reaction time. This will cause an increase of the densities and a decrease of the flows and the speeds. However, vehicles escaping

accidents at the beginning of the highway will travel at higher speeds on the final stretches of the road as they encounter lower traffic densities.

While the simple model proposed in this study appears to generate plausible behavior under various situations that are of particular relevance to extreme conditions, many improvements to the model are possible. For instance, the model still assumes that every driver keeps the same characteristics across the simulation time. The variance of reaction times, acceleration and deceleration rates, and desired velocities is only considered across drivers. Moreover, lateral movement is not captured in this study. Accordingly, lane changing maneuvers are not modeled explicitly.

5.3. Future Research Needs

This study is only addressing driver behavior on a two-lane freeway section. The individual characteristics are only affecting aggregate traffic properties on this section. The next step would be to implement the model on a more developed transportation network. Intersections and interchanges should be added. Additionally, a more extensive study can be conducted on the change of the flow-density-speed relationships under panic conditions.

On the other hand, the output generated by the proposed microscopic model is only compared with NG-SIM data collected under normal peak hour traffic situation. Data collected under panic situations like earthquakes is not available. For this reason, a full validation of the model remains an important goal that future research should seek to achieve.

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CURRICULUM VITAE

Samer Hani Hamdar was born in Beirut, Lebanon, on July 12, 1981, the son of Hani Ali Hamdar and Zeinab Mouhammad Hamdar. After completing his work at “Lycee Abdel-Kader” School in Beirut, Lebanon, he got his “French Baccalaureat” in June 1999. He entered The American University of Beirut in September 1999. He received the degree of Bachelor of Engineering in Civil and Environmental Engineering from The American University of Beirut in June, 2003. In September, 2003, he entered the Graduate School of The University of Maryland, College Park.

Permanent Address: Bourj Abou Haidar Street
 Horr Center, Block A, 12th Floor
 Beirut, Lebanon

This thesis was typed by Samer Hani Hamdar.