DEVELOPMENT OF AN ACCELERATION MODEL FOR TRAFFIC STREAMS HAVING WEAK LANE DISCIPLINE

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I hereby declare that the research work presented in this thesis submitted to the department of Civil Engineering, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh has been performed by me and this report or any part of it has not been submitted elsewhere for any other purposes except for publication.

July, 2013

Md. Mozahidul Islam

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ABSTRACT

In Bangladesh and especially in Dhaka City, traffic congestion has been a persistent problem for over a decade. Several attempts have been made, particularly in recent years, to mitigate the congestion problem. However, the congestion situation has continued to deteriorate. In order to combat such a persisting setback a robust solution is required which will be effective, economically feasible and sustainable. Microscopic traffic simulation tools, which model individual driver maneuvers (e.g. car-following/acceleration, lateral movement, etc.) and deduce network condition from those, can be used as laboratories for testing effectiveness of candidate traffic improvement initiatives before their actual field implementation. These tools are therefore increasingly being popular worldwide for selecting the most effective transport planning scheme and evaluate its economic feasibility.

Acceleration is an important driving maneuver which has been significantly modeled to work as a component of micro-simulation tools for several decades. The models are mainly developed for homogeneous motorized traffic where strict lane discipline is maintained. But when traffic stream also comprises non-motorized traffic and lane discipline is barely maintained, the conventional acceleration models developed for homogeneous traffic can no longer be effective. In the previous researches involving acceleration behavior in mixed traffic with 'weak' lane discipline, only one front or lead vehicle has been used to develop stimulus-response concept based acceleration models. This thesis proposes an updated acceleration model that captures the effect of more than one front vehicle (which is frequently found in the traffic streams with weak lane discipline) and aims to better replicate real traffic situations.

The acceleration model proposed in this research uses an econometrics based approach. The data used for developing these models have been collected from two locations of Dhaka City; Kalabagan and Shukrabad using video cameras mounted on over-bridges. GPS equipped vehicles were run as well in a pre-specified route including these locations in order to supplement the video data. Image processing software 'TRAZER' (KritiKal Solutions Pvt. Ltd.) was used to perform vehicle count, measure average speed and flow and provide trajectory data. The data was then fed into 'MATLAB' code and the input variables for the model were generated. A number of models were run using statistical software 'STATA SE 11' to obtain the best model in terms of variables involved and model result. The effect of reaction time on acceleration/deceleration maneuver of drivers has also been analyzed in this regard. At the end, two distinct models, one for acceleration and one for deceleration maneuvers have been developed. The models, when plugged in a microscopic traffic simulator, can be used to predict the possible actions for a set of factors (independent variables) which directly affect the acceleration and deceleration decisions of drivers in traffic streams with weak lane discipline.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF NOTATIONS AND ABBREVIATIONS

Acc	Acceleration
Dec	Deceleration
VEHFOL	Vehicle-Following Model
LMV	Light Motor Vehicles
HMV	Heavy Motor Vehicles
SUV	Sport Utility Vehicle
PCU	Passenger Car Unit
MATLAB	Matrix Laboratory
TRAZER	Traffic Analyzer and Enumerator
GM	General Motors

Chapter 1

Introduction

1.1 Background

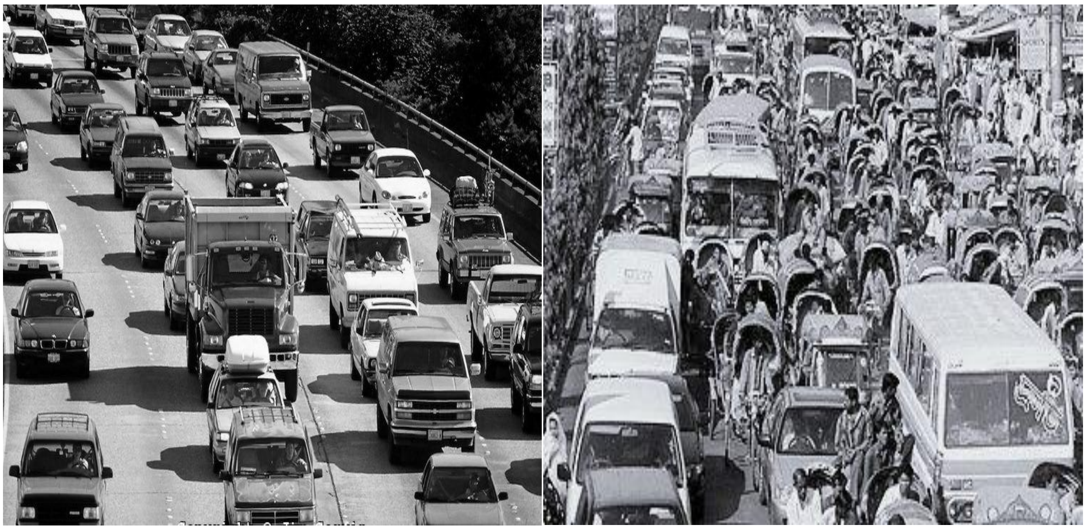
In Bangladesh, especially in Dhaka city, traffic congestion has been a chronic problem and is a hindrance for the socio-economic development of the country. The alarming traffic growth rate and mismanagement over the transportation sector has substantially deteriorated the situation. In order to combat such a persisting setback a robust solution is required which will be effective, economically feasible and sustainable. Microscopic traffic simulation tools, which model individual driver maneuvers (e.g. car-following/acceleration, lateral movement, etc.) and deduce network condition from those, can be used as laboratories for testing effectiveness of candidate traffic improvement initiatives before their actual field implementation. These tools are therefore increasingly being popular worldwide for selecting the most effective transport planning scheme and evaluate its economic feasibility.

Acceleration is an important driving maneuver and is a prime mechanism which has been significantly modeled to work as a component of micro-simulation tools for several decades. This type of research has been conducted for homogeneous traffic condition particularly in developed countries. The developed models may be grouped as car-following model (e.g. Chandler et al, 1958; Gazis et al., 1959; Edie, 1961, Gazis et al., 1961; Herman and Rothery, 1965; Ozaki, 1993; Ahmed, 1999, Choudhury et al, 2009, etc.), psychophysical model (e.g. Ludmann et al., 1997; Schulze and Fliess, 1997; Brackstone et al., 2002, etc.), fuzzy-logic model (e.g. Kikuchi and Chakroborty, 1992; Brackstone et al., 1997, Chakroborty and Kikuchi, 2003, etc.), cellular automata model (e.g.Wolfram, 1986, Nagel and Schreckenberg, 1992; Hafstein et al., 2004, etc.), and general acceleration model (e.g. Gipps, 1981; Benekohal and Treiterer, 1988; Yang and Koutsopoulos, 1996; Ahmed, 1999 and Hidas, 2002). The models range from simplest car-following model (Chandler, 1958) with minimum parameters, to comparatively complex and comprehensive model (Hafstein et al., 2004) with multi-variable consideration.

There are a number of limitations of state-of-the-art acceleration models. According to Kim et al. (2003), some acceleration models (e.g. Chandler, 1958; Gazis, 1958; Edie, 1961; Herman and Rothery, 1965, Gipps, 1981, etc.) are based on the assumption that drivers follow the same driving rules. In fact, these rules may differ with different drivers, or even for the same driver and with different conditions, and in fact, possibly with the same driver and nearly identical situations. Some other limitations include absence of significant stochastic components, ignorance of factors beyond vehicle kinematics and ignorance of past sequence of car motion that produce the current state and the inadequacy to represent the normal car-following behavior.

The most important setback is that as these models are developed for homogeneous lane-based traffic (Figure 1.1a), they cannot be directly applied to heterogeneous traffic stream which are characterized by the following (Figure 1.1b).

1. Presence of non-motorized traffic and therefore difference in speed between the motorized and non-motorized vehicles
2. Weak lane discipline



(a) (b)

Figure 1.1: (a) Homogeneous traffic of California (b) Heterogeneous traffic of Dhaka

Unfortunately, the research work on modeling heterogeneous traffic stream is quite few. The research of Mallikarjuna (2007) has focused on the analysis and modeling of heterogeneous traffic observed on mid-block sections of urban and rural roads of India. Models have also been developed for heterogeneous traffic at controlled intersections (e.g. Maini, 2001). Some studies have attempted to identify the effect of lead-vehicle size on driver-following behavior in mixed traffic stream (e.g. Sayer et al., 2003; Ravishankar and Mathew, 2011). Another study by Gunay (2007) has tried to conjugate the longitudinal movement with lateral movement to define the lateral discomfort while longitudinal movement is in action.

In Bangladesh, the research of Imran (2009) has focused on development of car-following model for mixed traffic using fuzzy-logic inference system of MATLAB. Earlier, there has been research on modeling heterogeneous traffic operations at two corridors of Dhaka city (e.g. Hossain, 1996). In this study, the effect of different composition of non-motorized traffic on corridor travel time and passenger movement capacity has been analyzed based on the developed simulation model (MIXNETSIM) (Hossain, 1996). Moreover, some factors have been identified (e.g. traffic density) which may result in higher delay for traffic for larger size vehicles. The research of

Hoque (1994) was mainly on modeling of signalized intersections of Dhaka city. This model (MIXSIM) has been used in computation of PCU conversion factor and evaluation of alternative schemes to improve the capacity of an approach serving mixed traffic flow.

There exist some notable drawbacks in the existing acceleration models for heterogeneous traffic (which are discussed in detail in Chapter 2). The identification of lead vehicle is not well defined yet. The effect type of lead and following vehicle on vehicle following behavior has not been covered either. Moreover, the complete stability analysis of car-following model has yet to be studied. At last, but not the least, the limitations discussed above for literatures on homogeneous traffic are also applicable for heterogeneous traffic as well. The more research on this field may unveil the new challenges and usher the way for new thoughts and techniques to proceed further.

1.2 Objectives

The overall objective of this research is to develop an acceleration model with special focus on situation with weak lane discipline and calibrate the model parameters using detailed data collected from selected locations of Dhaka city. The specific objectives are:

- Development of acceleration model structure
- Collection and processing of comprehensive disaggregate (e.g. second by second trajectory data) and aggregate data (e.g. traffic counts and speeds) to calibrate the proposed model structure
- Calibrate the proposed model using econometric approaches

1.3 Scope

The scope of this study is to develop an acceleration model for mixed traffic of Dhaka city. The model will be an econometric model and will be based on stimulus-response concept of car-following mechanism. Detailed data will consist of disaggregate and aggregate data from a number of locations of this city. The data will cover the necessary information to identify the position of vehicles and will produce trajectories for a pre-defined period. In the first stage, the data will be used to generate the speed and acceleration of vehicles with time. The acceleration decisions will be arranged sequentially to get an acceleration profile of the driver. This acceleration profile can give insight about the driving behavior of a person (longitudinal movement) for a set of vehicle characteristics and demographic attributes.

At the second stage the model equation will be developed and the parameters will be estimated using disaggregate data to show the relationship between the acceleration (or, deceleration) rate of the drivers and the factors affecting the decision (acceleration or, deceleration). The database may be expanded later to make the model more reliable and for possible modifications to reflect the longitudinal movement of driver more realistically. This type of acceleration models may be combined with lateral movement models to understand the driving pattern in a more logical way. The combined model then can be run in simulation tools to replicate the driving behavior for mixed traffic conditions with varying proportion of motorized and non-motorized traffic. The transport planners and policy makers may be interested in such practice to make new plans or policy for traffic improvement and management scheme (e.g. reduction of congestion, effect of construction of new transport infrastructure on traffic movement prior to implementation).

1.4 Organization

This thesis comprises of seven chapters to illustrate the methodology for achieving the aforementioned objectives. The thesis is organized as below.

- Chapter 1 gives the context of the study in a nutshell
- Chapter 2 focuses on the review of the previous thesis papers and other sources related to this topic by comparison of different approaches, cross referencing, recommendation and necessary citations
- Chapter 3 describes the model structure developed for thesis and also the challenges for modeling acceleration behavior of heterogeneous traffic streams
- Chapter 4 highlights on data collection prior to model development
- Chapter 5 illustrates the analysis of data and subsequent model development using this data
- Chapter 6 presents the conclusion of the entire study, identifies potential applications and provides suggestions and recommendations for further development of the work

Chapter 2

Literature Review

2.1 General

Driving behavior models represent the maneuver of drivers in roads while driving in different roadway and traffic condition. There are a number of such models to represent the behavior of drivers which have been developed for more than half a century. Though there are models for almost all types of driving operations, acceleration models for longitudinal movement are predominant followed by lane-changing models and other models (e.g. models for merging and crossing). In the following subsections a detailed description of the acceleration models for homogeneous and heterogeneous traffic will be presented.

2.2 Acceleration Models for Homogeneous Traffic

There have been numerous works on acceleration behavior of drivers in homogeneous traffic condition where lane discipline is maintained. Homogeneous traffic means the traffic stream consists of only motorized traffic. Lane discipline accounts for the compliance of drivers to remain in the same lane for a particular link (midsection of road between two consecutive intersections) of road.

Depending on the spacing between vehicles and the driver's freedom to attain the target speed driving condition may be classified as three distinct regimes. Regime one stands for the situation when the driver has the freedom to acquire its desired or target speed as there is very lean density of traffic on the road. This driving condition is referred as 'free flow' regime and the driver does not actually follow any other vehicle. The second regime called 'car-following regime' accounts for the following nature of vehicle drivers as they move in longitudinal direction along the roadway. The spacing between vehicles is such that it does not allow the drivers to accelerate indefinitely according to drivers will and therefore the drivers are restricted to follow their front vehicles. There is another driving regime known as 'emergency regime' which is another form of car-following regime but the density of traffic is high and stop-and-go situation prevails. So there is little scope to even accelerate within a short period and makes the drivers impatient at some cases.

Acceleration models can fall into different groups depending on the driving situations the models deal with. In this thesis mainly the literatures regarding car-following behavior of drivers will be described from section to 2.2.1 to 2.2.4.

2.2.1 Car-Following Models

The concept of car following was first proposed by Reuschel (1950) and Pipes (1953). Car following models describe the interaction between adjacent vehicles in the same lane (Brackstone and McDonald, 1999).The subject vehicle follows the leader (vehicle in front) and responds to its action. These models are the major parts of the microscopic vehicular movements modeling which provide the foundation for traffic simulation systems.

Car-following models may further be divided into a number of sub-models like stimulus-response model, collision-avoidance model and psychophysical model.

2.2.1.1 Stimulus-response models

Stimulus-response models have been developed based on the assumption that the driver decision to accelerate or decelerate is actually a response. The stimulus which prompts the drivers to make such a response may be a number of factors starting from the action of the front or lead vehicles to the incident occurred in the road ahead of the driver under consideration. The widely known stimulus-response model is General Motors non-linear model or GM Model.

The GM Models (Brackstone and Mc Donald, 1999) were developed from a series of studies conducted at the General Motors research laboratories in Detroit in the late 1950s (Chandler et al., 1958; Gazis et al., 1959; Gazis et al., 1961). Researchers at the GM Research Laboratory introduced the sensitivity-stimulus framework that is the basis for most car following models to date (Toledo, 2003). According to this framework a driver reacts to stimuli from the environment. The response of the driver is given by

$$\text{response}(t) = \text{sensitivity}(t) \times \text{stimulus}(t-\tau)$$

Where, t is the time of observation and τ is the reaction time for drivers. The time interval between seeing, hearing, or feeling and the starting to do something in response to the stimulus of a traffic or highway situation are called “reaction time”. The psychological process constitutes four operations; perception, identification or intellection, emotion or judgment and volition or reaction (means execution of decision).

2.2.1.2 Collision avoidance models

Now-a-days a more advanced acceleration models are used to represent car-following behavior of driverswhich rectifies the limitations of the stimulus-response models. Collision-avoidance model is one of them.

The collision avoidance models assume that the following vehicle will maintain a safety distance to the vehicle in front and will select its speed to ensure the vehicle can stop safely to avoid a rear-end collision (Lee, 2007). Such models (e.g. Kometani and Sasaki, 1959; Gipps, 1981) are developed based on the equations of motion. This type of model has been criticized as the following vehicle cannot react in time when the leading vehicle performs a sudden break or deceleration. To facilitate a clear conscious view of vehicular flow characteristics Gipps (1981) developed a model in which extra safety reaction time and safety headway margin were introduced. No calibration of parameters was required for this model. The model was able to reflect the real traffic flow characteristics when realistic values were assigned to the parameters.

The advantage of collision avoidance model is that longitudinal and lateral movement of vehicle both can be described by this model after a few adaptations. Gunay (2007) tried to integrate the lateral offset of the following vehicle into the Gipps (1981) following model. This study was a pioneer to describe the two-dimensional movement of cars. This model can allow flexibility to alter kinematic properties as well.

The greatest challenge to the validity of collision avoidance model emerged when it was appeared that Newtonian mechanics could fail to illustrate a short headway. This suspicion arouse when Brackstone et al. (2002) found that the minimum desired following distance was far lower than believed when they investigated the parameters for the action point model. In fact, it is obvious that a driver should be vigilant while following a vehicle closely and the reaction time will be less than usual. An extremely short headway can be described by a collision avoidance model if the driver expects a low deceleration difference to the preceding vehicle (Lee, 2007).

2.2.1.3 Psychophysical models

The psychophysical model, developed by Weidmann(1974) and Leutzbach(1988), assume that the drivers of the following vehicles follow the leaders even when the space headway is large and they fabricate a perception threshold to avoid any kind of collision. The concept was first brought up by Michaels (1963).A vehicle driver wants to drive to his target or desired speed in free flow condition. The response of the driver is influenced by the perception threshold on a large scale. In fact, the term “perception threshold” works in two mutually related and subsequent operations. First of all, a driver will increase the speed until he realizes that the further increment will be venturesome enough to cause a rear end collision. Then he will try to maintain the speed with the leading vehicle. It is not always possible to maintain the equal space or time headway all the time. In the second case, when the preceding vehicle will be far beyond the perception threshold or space headway will increase significantly, the same driver of the following vehicle will try to accelerate his vehicle and reduce the headway and maintain equal speed to that of the leader. The mechanisms are periodic and termed as “following spiral”. As following and leading vehicles are totally relative to each other, there is no way to stop the cycle. As a result, the psychophysical model is able to illustrate the oscillating phenomenon observed in car following experiments. The perception threshold was found from a number of acceleration and deceleration decisions made by the drivers. For probably being somewhat psychological, no rigorous framework for calibrating the model has been proposed yet.

2.2.2 General Acceleration Models

General acceleration models are special form of acceleration models which can represent the driving behavior in both car-following and free-flow regime.

Gipps (1981) developed the first general acceleration model. The maximum applicable acceleration is based on two constraints: speed and headway. It is assumed that the speed may not exceed its desired value and the minimum safe headway must be kept. The safe headway is the minimum distance that is required for the following vehicle to avoid a collision when the leading vehicle reduces its speed abruptly by applying emergency braking. Calculations are based in the equations of laws of motion. The vehicles are characterized through the upper bounds of acceleration and deceleration values.

A similar model for CARSIM tool was developed by Benekohal and Treiterar (1988). In this model acceleration is calculated separately for five different situations. Yang and Koutsopoulos (1996) developed a general acceleration model and implemented it in MITSIM, a microscopic traffic simulator. The driver is assigned to one of three regimes based on time headway: emergency regime, car following regime and free-flow regime. Zhang et al. (1998) implemented a multi-regime acceleration model in MRS, a microscopic traffic simulator. They define several different driving regimes based on space headways. The regimes are emergency, normal car following, uncomfortable car following and free flow. When the space headway is smaller than a pre-specified threshold value, it is termed to be emergency regime. Normal car following model uses the non-linear GM model (Gazis et al. 1959). Uncomfortable car following is applied when the acceleration calculated by normal car following is positive and the headway is positive based on Pipes' definition (1953). In this case the driver applies a normal deceleration instead of normal acceleration. Normal accelerations and decelerations are also applied in free-flow regime in an attempt to attain the desired speed. Ludmann et al. (1997) used similar driving regimes in the microscopic traffic simulator PELOPS. Ahmed (1999) proposed a modification over Modified GM Model and new model which is capable of representing free-flow and car-following regime. Apart from the parameters of Modified GM Model (Gazis, 1961) the newly developed model incorporates traffic density, uses non-linear term for relative speed and an error term. The models have been calibrated for reaction time of zero and 1 second and model parameters have been estimated for acceleration and deceleration situation separately.

2.3 Acceleration Models for Heterogeneous Traffic

The research on modeling heterogeneous traffic is comparatively less than that of homogeneous traffic. Heterogeneous traffic stream consists of both motorized and non-motorized vehicles and in almost all cases lane discipline is not properly maintained. There is heterogeneity in terms of vehicle types and drivers. Heterogeneous traffic is mainly noticed in developing countries (e.g. Bangladesh, India). Due to the growing needs of acceleration models for heterogeneous traffic, the research is expanding. In this section the previous works on modeling acceleration behavior of drivers in heterogeneous traffic conditions will be discussed.

2.3.1 Vehicle-Following Model (VEHFOL)

The model was developed by Maini (2001). Vehicle-following is the king-pin of a microscopic traffic simulation model. A vehicle-following model describes the response of a following vehicle based on an action or stimulus of the lead vehicle. The condition is that the following vehicle's lateral movement should be restricted and there will be no scope to overtake the front (lead) vehicle.

There are three governing principles for a following vehicle in most vehicle-following models. These are given as below,

- Achieving a minimum gap with the shortest possible time and at a comfortable speed
- Avoiding collision with the lead vehicle even when the lead vehicle applies emergency brake
- Maintaining minimum gap after its attainment by the following vehicle

There are some drawbacks in the previous and contemporary vehicle-following models like the consideration of inadequate number of variables in formulating model equation, assumption regarding the application of brakes of the following vehicle and focusing on the long term goal of following vehicle without monitoring the movement of the leader at every second. In some cases, the generalized equation solution results in a steady state velocity that is either negative or is either greater than the maximum velocity of the vehicle. The acceleration rate in some cases has been found extremely high and unrealistic as the following vehicle approaches to the steady state.

In order to address the aforementioned drawbacks, VEHFOL has been developed. The basic premises of VEHFOL are as follows,

- A following vehicle reacts to the stimulus only after it perceives the stimulus.
- If the velocity of the following vehicle matches with the velocity of the lead vehicle and minimum gap is maintained, the following vehicle attempts to achieve a steady state.
- After the attainment of the steady state, the following vehicle attempts to maintain the minimum distance gap (based on minimum time gap) with the

lead vehicle. The constraint of equal velocity is no longer applied significantly.

One important feature of VEHFOL is that the reaction time of the following vehicle, c, is explicitly considered while determining the action of the following vehicle. A reaction time of 0.5 seconds has been considered in VEHFOL.

The acceleration rate of the following vehicle is limited by the following limiting value

- Applied acceleration rate ≤ Maximum acceleration rate of the vehicle
- Applied deceleration rate ≥ Maximum deceleration rate of the vehicle
- Velocity resulted from the applied acceleration rate ≤ Maximum velocity of the vehicle

In order to examine the performance of the vehicle-following model (VEHFOL), 31 specific cases of vehicle-following were identifiedat thirteen intersection approaches (at five intersections) and at four mid-block locations in New Delhi and Baroda. Each following vehicle was influenced by only one lead vehicle in all cases. The period of vehicle following vehicle-following ranged from 4 to 17 seconds (total time of vehicle following was 286 seconds).

Three vehicle-following modes were constituted from the vehicle-following data. These are accelerating, decelerating and flow during green mode. The accelerating mode refers to the departure of the vehicles from the stop line of intersection approach. The decelerating mode stands for the movement of vehicle before reaching the stop line of the approach when the signal is red. The flow during green mode indicates the free flowing condition of vehicle movement through the intersection when the signal is green in the approach.

2.3.2 Other Models

Ravishankar and Matthew (2011) worked on the car-following behavior of vehicles in heterogeneous traffic streams consisting of diverse vehicle types with very weak lane discipline in India. They actually focused on the incorporation of some vehicle type dependent parameters to modify Gipps' (1981) Model in order to better represent the following behavior of vehicles. Performance of the model was studied for both microscopic and macroscopic level using data collected from both homogeneous (for car and truck combination) and heterogeneous traffic stream (with three vehicle types like bus, car and three wheeled auto-rickshaw consisting of nine vehicle pair combinations). The subject vehicles were with GPS devices to get their trajectories. The drivers were regular drivers and not aware of the objective of the study in order to get the actions occurring in reality. The results of the study showed that passenger car following another passenger car combination gave higher mean speed due to the higher acceleration capabilities of these types of vehicles. In a similar way, three wheeled auto-rickshaw involvement as lead or following vehicle resulted in lesser mean speed. The study also found that the following distance was also affected by the vehicle pair as auto-rickshaw following another auto-rickshaw maintained a gap of 9.68 m while car-bus pair used a gap of 25.47 m, a significantly larger value.

Oketch (2000) made an attempt to formulate a different modeling approach for modeling heterogeneous traffic including non-motorized traffic. The study was carried out at Uhuru Highway of Nairobi in Kenya. A car-following model was adopted in this study similar to that proposed in Gipps (1981) model. Both longitudinal and lateral movements were considered in this study (two-dimensional movement). The lateral movement was taken as gradual process instead of an instantaneous one. This study acknowledged the type of the lead and following vehicles while maintaining a longitudinal gap (in motion and standstill state) and while performing overtaking. Seepage of some types of vehicles like bi-cycle, motorcycle and three wheeled auto-rickshaw while in queue was analyzed as well. The model was developed using fuzzy-logic. The study finds that the vehicles which require mandatory lane-changing may not follow conventional car-following rules and often exhibits abnormal behavior. The research initially identified the vehicles which do not require lane changing. Then the impatience of drivers was observed that was marked by frustration. The vehicle drivers out of frustration were identified as vehicles to be in compliance with car-following rules. The cycle was repeated to identify the vehicles which are actually going for lane changing and car-following action separately but in a dynamic process. The developed model could predict the queue length, mid-link speed, value of delay and link travel times with reasonable accuracy, as the maximum error was only 5.3 percent.

2.4 Limitations of State-of-the Art Acceleration Models

In the following sections the limitations of state-of-the-art acceleration models for both homogeneous traffic and heterogeneous traffic are described.

2.4.1 Limitations of the Acceleration Models for Homogeneous Traffic

The drawbacks of state-of-the-art acceleration models for homogeneous traffic are given as below,

Compliance of driving rules: While developing the acceleration models it has been assumed that the drivers in a traffic stream obey traffic rules. But the actual scenario is quite different. In fact, these rules may differ with different drivers, or even for the same driver and with different conditions, and in some cases, possibly with the same driver and nearly identical situations.

Stochastic component of models: Most of the modelsuse only a set of kinematic variables, such as relative spacing and speeds, instantaneous speeds,, etc., to determine subsequent driving behavior ((Kim et al., 2003). In fact, there are numerous other factors besides basic kinematics that may influence car-following behavior, such as various human characteristics (e.g., gender, age, and environmental conditions like mobile phone usage, vehicle occupancy (distraction level)), traffic and road characteristics (e.g., type of vehicle, type of roadway and geometric condition, congestion level, and number of lanes or location of driving lane), and environmental characteristics (weather condition, time of day or day of week, and area type). So it can be said that a number of significant stochastic components are missing from some state-of-the-art acceleration models (Kim et al., 2003).

Past sequence of car-motion: The past sequences of driving eventually produce the current state of driving but in some literatures this notion is completely overlooked by considering that the decision is instantaneous (Kim et al., 2003) Although a reaction time is considered in stimulus-response model but it is not adequate in representing the past sequence (historical evidence). Therefore the most natural following response might differ in actual case.

Representation of car-following behavior: The representation of normal car-following behavior is inadequate in some literatures (Kim et al., 2003).

2.4.2 Limitations of the Acceleration Models for Heterogeneous Traffic

The limitations of state-of-the-art acceleration models for homogeneous traffic are given as below,

Effect of vehicle type: The type of both the front and subject vehicles affect the acceleration behavior of subject vehicle drivers. But in the previous researches regarding development of acceleration model for heterogeneous traffic this effect has not been addressed.

Identification of lead vehicle: In heterogeneous traffic condition the following scenario is very common (Figure 2.1).

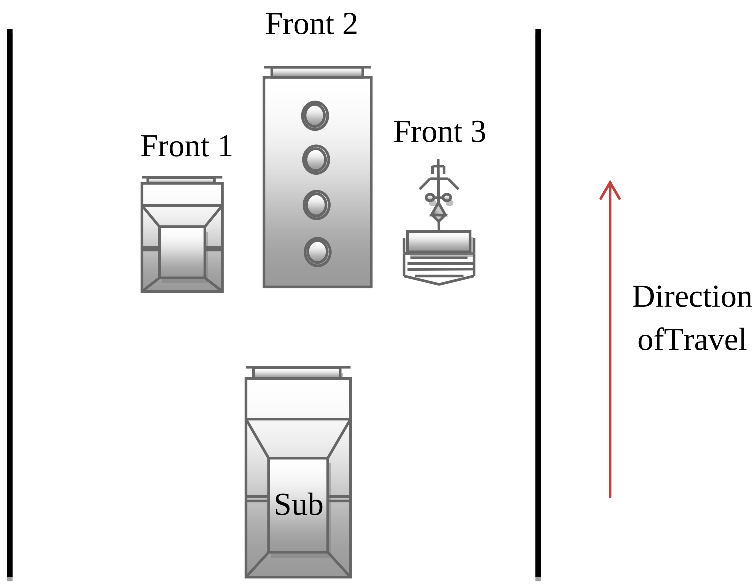


Figure 2.1: Multiple front vehicle of one subject vehicle

From figure 2.1 it is seen that, in heterogeneous traffic stream with weak lane discipline, there may be more than one front vehicle (here 3 front vehicles; one car, one bus and one rickshaw) for a subject vehicle (car). The methodology for identification of lead vehicle from these three front vehicles has not been discussed in previous research works

Lateral movement effect: The continuous lateral movement of the vehicle is a common feature in a traffic stream where lane discipline is weak. This type of movement has effect on the acceleration maneuver of the vehicle. But this phenomenon has not been discussed in the previous works.

2.5 Summary

In this chapter a number of acceleration models developed for homogeneous and heterogeneous traffic have been briefly discussed. It has been seen that the number of acceleration models developed for heterogeneous traffic is significantly less than the acceleration models developed for homogeneous lane based traffic. The acceleration models for heterogeneous traffic has several limitations like overlooking the effect of the type of lead and following (subject) vehicle on the following behavior, absence of proper methodology to identify lead vehicle from multiple front vehicles, and failing to address the effect of human factors (age, gender, driving experience). These limitations make it difficult to use the conventional models in traffic simulations of Dhaka and other cities of developing countries.

Chapter 3

Model Structure

3.1 General

The previous chapter has focused on some acceleration models developed for homogeneous and heterogeneous traffic. It has been found that due to the difference of nature of homogeneous and heterogeneous traffic, the decisions taken by a driver also differs with type of vehicle and the driver's own demographic characteristics. The following section of this chapter will demonstrate the main challenges behind the modeling of heterogeneous traffic weak lane discipline of drivers.

3.2 Challenges for Modeling Acceleration Behavior of Heterogeneous Traffic Streams

The acceleration models for both homogeneous and heterogeneous traffic have a number of limitations in terms of methodology and illustration. In this thesis, the challenges for modeling heterogeneous traffic will be discussed only. The challenges are given as below,

Variation of speed and acceleration: Heterogeneous traffic stream consists of both motorized and non-motorized vehicle and therefore has a significant variation in the maneuverability of these vehicles. The dynamic characteristics (e.g. speed, acceleration) are different as well. As a result the complexity is augmented which makes the modeling task challenging.

Absence of lane marking: In some roads there is no lane marking and thus it is difficult to represent the flow.

Weak lane discipline: Apart from the heterogeneity in maneuverability and dynamic characteristics, the vehicles maintain poor lane discipline and therefore it becomes difficult to identify the leader in all circumstances.

Reliability of data: In homogeneous traffic the lateral position of traffic may not be a major concern as strict lane discipline is maintained. But in heterogeneous traffic condition where lane discipline is poorly maintained or not maintained at all, it becomes a difficult task for image processing software to maintain accuracy as lateral position also becomes a matter of concern.

In order to make a rigorous acceleration model for heterogeneous traffic stream the above challenges need to be overcome at first place. Some modification over the state-of-the-art acceleration model especially developed for homogeneous traffic may be considered as well.

3.3 Proposed Model Structure

A state-of-the-art, non-linear stimulus-response model known as 'General Motors Non-linear Model (GM Model)' proposed by Gazis (1961) has been considered as the base model for this thesis. This model is widely used and suitable to represent car-following nature of vehicles. The basic structure of the model is as follows,

$$a = \alpha * (X_1)^{\beta 1} * (X_2)^{\beta 2} \ldots (Xi)^{\beta i} \ldots (Xn)^{\beta n}$$

or,

$$a = \alpha * \prod_{i=1}^{n} X_i$$

Where,

a= Acceleration of subject vehicle

i = identifier of the variable number (i = 1, 2, 3, … , n)

X_i = Variable affecting acceleration of subject vehicle (e.g. velocity of subject vehicle, front relative speed, front relative spacing, etc.)

α = constant

β = parameter associated with X_i

Since it is not always possible to identify a distinct lead vehicle in weak lane situations, the basic structure can be expanded as follows,

$$a = \sum_{j=1}^{3} \prod_{i=1}^{n} \alpha_{ij} * (X_{ij})^{\beta ij}$$

Where,

j = identifier for front vehicles (j= 1 to 3 as maximum three front vehicles will be considered)

and α_{ij} and β_{ij} are used for estimation using non-linear regression approach.

It may be noted that due to unobserved variables and unobserved heterogeneity, there exists an error term in this type of model. The non-linear regression approach has been used to minimize this error (difference between observed and fitted acceleration).

In order to replicate the real world driving behavior some unquantifiable variables (factors) should be used alongside the quantifiable variables (e.g. space headway, subject speed and the relative speed between subject vehicle and front vehicle) already used in Modified GM model.

The other variables which affect car-following behavior of subject vehicle have been identified from previous literatures (e.g. Sayer et al., 2003; Ravishankar and Mathew, 2011; Gunay, 2007, etc.). The potential new variables are,

(i) Type of subject vehicle: static and dynamic characteristics like stopped and moving longitudinal and lateral gap, maximum acceleration, maximum deceleration, maximum speed which depends on the type vehicle and interaction between vehicle pair
(ii) Type of neighboring vehicles: presence of large/heavy vehicle in front of and behind the subject vehicle
(iii) Traffic measurement: density of traffic on the link
(iv) Free flow speed distribution: variation in free flow speed consideration depending on vehicular, roadway and driver characteristics
(v) Roadway Characteristics: grade of road surface and surface condition (rich or poor surface texture)
(vi) Weather condition: various weather variations like day/night time, foggy/sunny/snowfall/rainfall events, etc.

These variables need to be converted to explanatory variables in order to incorporate in acceleration model.

For heterogeneous traffic, the bumper to bumper distance (true gap) between pairs of vehicles (front and subject vehicle) may be adopted in lieu of front bumper to front bumper distance in compliance with Modified GM Model. All of the variables will not be possible to incorporate with Modified GM Model. This thesis will try to incorporate the type of the subject vehicle and neighboring vehicles and other related parameters for the proposed model.

The parameters of the Modified GM Model will be used to formulate the proposed model. Actually, two distinct model equations will be formed in order to replicate acceleration and deceleration behavior. Therefore two different datasets; acceleration data and deceleration data will be collected. The datasets will be generated from raw primary data (especially trajectory data). The effect of reaction time will be shown before the actual test run for selection of appropriate acceleration and deceleration models.

3.4 Proposed Implementation Framework

A vehicle driver performs several operations in movement along the road (e.g. longitudinal movement, lateral movement, merging, weaving, etc.). Acceleration decision is a prime factor for representing the longitudinal movement of any vehicle in the road. The application of acceleration or deceleration depends on a number of factors like traffic density, presence of heavy vehicle, presence of slow-moving vehicle, etc. In this research, the acceleration behavior of driver will be highlighted for longitudinal movement only.

The flow chart for acceleration decision in longitudinal direction is depicted in figure 3.1.Necessary demonstration and illustration are provided as well in the following sections.

3.4.1 Hypothesis

A vehicle's movement in most cases is not a uniform one. It falls in different states on its way of travel. The decisions taken by a vehicle driver also differs in compliance with the condition. The different states of driving will be termed as 'driving regime' and used in this thesis for convenience.

In order to demonstrate and explain the acceleration algorithm three distance terms named safe distance, non-collision distance and critical non-collision distance will be used. The distances are hypothetical in nature and are assumed on the basis of the following consideration.

Safe distance (assumed)>non-collision distance>critical non-collision distance

All three distances are dependent on the characteristics of subject vehicle and lead vehicle (if any). The subject vehicle is the vehicle under consideration and the lead vehicle is the vehicle which is followed by the subject vehicle.

It is also assumed that, whatever might be the speed of the following vehicle (even in desired speed or the target speed), if the longitudinal headway (bumper to bumper distance of the vehicles along the road) with the leader is within $h_{freeflow}$ (free flow distance, detailed explanation is given later) it will be in car-following regime.

Moreover, it is considered that the subject vehicle in free flow regime moving with less than desired speed, will try to accelerate at maximum acceleration rate to attain desired speed as quickly as possible.

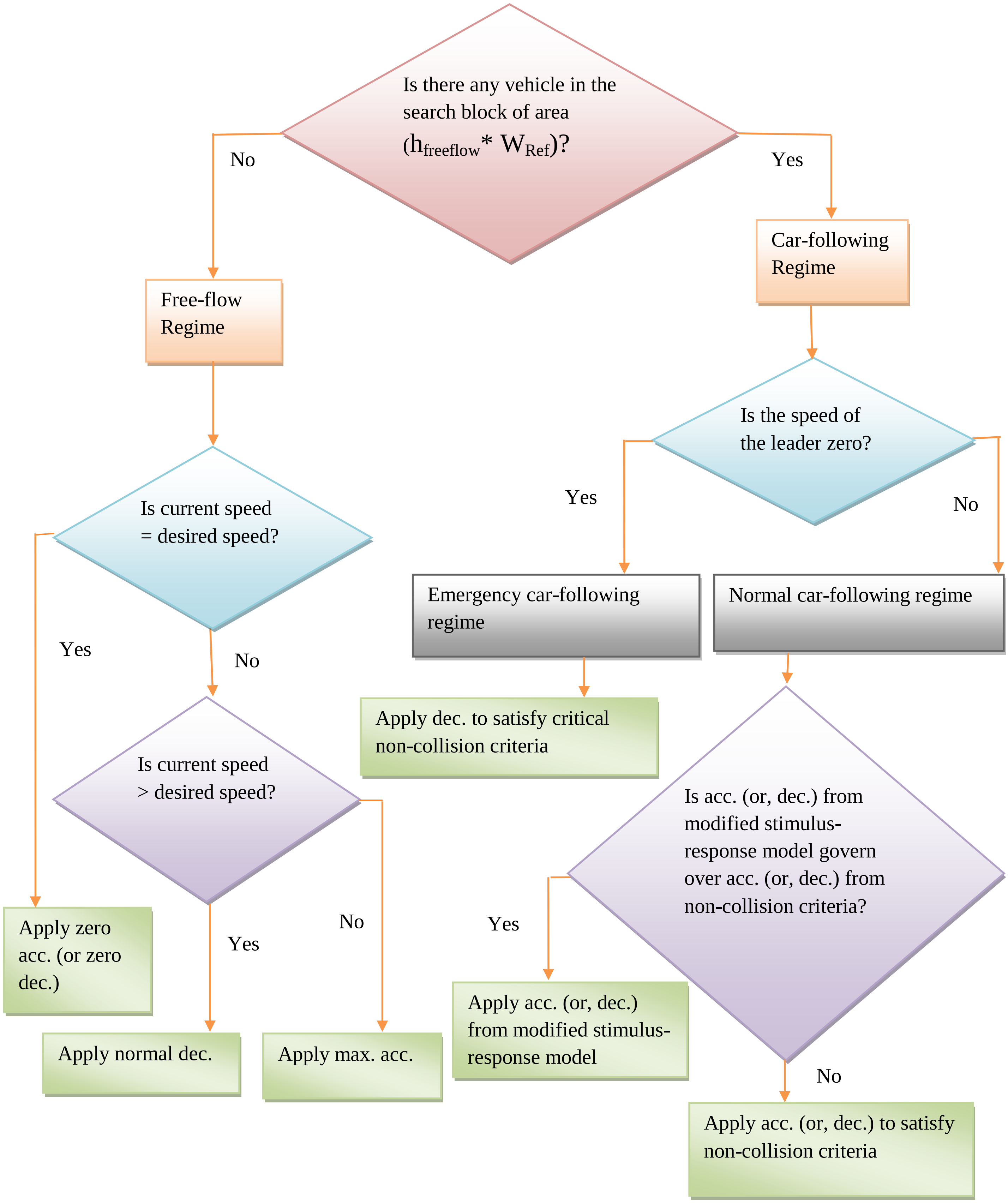


Figure 3.1: Flow-chart for acceleration (or deceleration) maneuver (without lateral movement consideration)

3.4.2 Illustrations of Different Terms (for Flow Chart)

There are a number of terms used in the previous chart. In the following sub-sections the terms will be clarified sequentially.

3.4.2.1 Search area width (W_{SA})

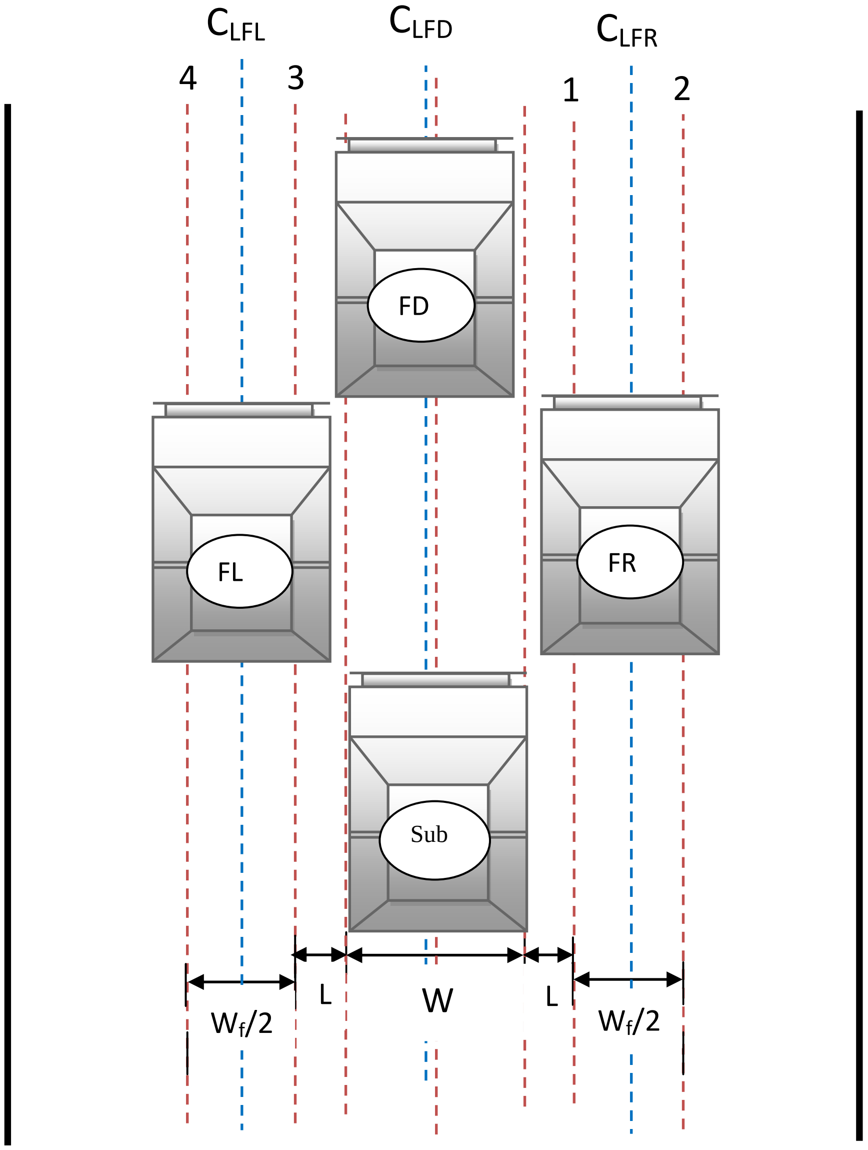


Figure 3.2: Search area width (W_{SA}) for selecting front vehicle for model

In figure 3.2 the position of subject vehicle (marked by ‘Sub’) and other vehicles have been shown. The width of the subject vehicle has been marked by W. On both sides of the subject vehicle a lateral clear gap (L) has been considered from safety point of view. In this thesis, this gap has been taken 0.5 meters for all types of vehicles. Moreover, additional lateral distance has been considered which will be varied according to the type of the front vehicle.The search area is denoted by the search area width multiplied by the longitudinal headway (0.3 second for this thesis). Any vehicle whose rear bumper is in front of the front bumper of the reference vehicle and inside the search area has been considered as front vehicle. More filtering has been done using the centerline concept. The front vehicle whose centerline is inside the width W+2L (between line 1 and 3) has been considered as the front direct vehicle in this thesis. If more than one vehicle satisfies this notion, then the most immediate vehicle has been considered.The criteria for defining the front right and the front left vehicle is similar. In order to identify these vehicles an additional width of $W_F/2$ has been used. W_F refers to the width of the front vehicle under consideration and therefore this dimension will vary. This variable dimension has been used in order to take into account the type of front vehicle. The lateral gap between line 1 and 2 and also line 3 and 4 defines this width. If the centerline of the front vehicle falls between line 1 and 2, and satisfies the longitudinal distance criterion (within 3 second), then it will be considered as the front right vehicle (if more than one vehicle satisfies this notion, then the most immediate will be considered). In a similar way the front left vehicle has been considered (centerline falls between line 3 and 4 satisfying longitudinal headway criterion and most immediate if more than one).

In order to clarify the above concept the four cases have been generated. The cases are depicted from figure 3.3a to 3.3d. It must be noted that in all cases the front vehicle satisfies the longitudinal headway criterion (0.3 second in this thesis).

Case 1

Subject vehicle is motorcycle and front vehicle is bus

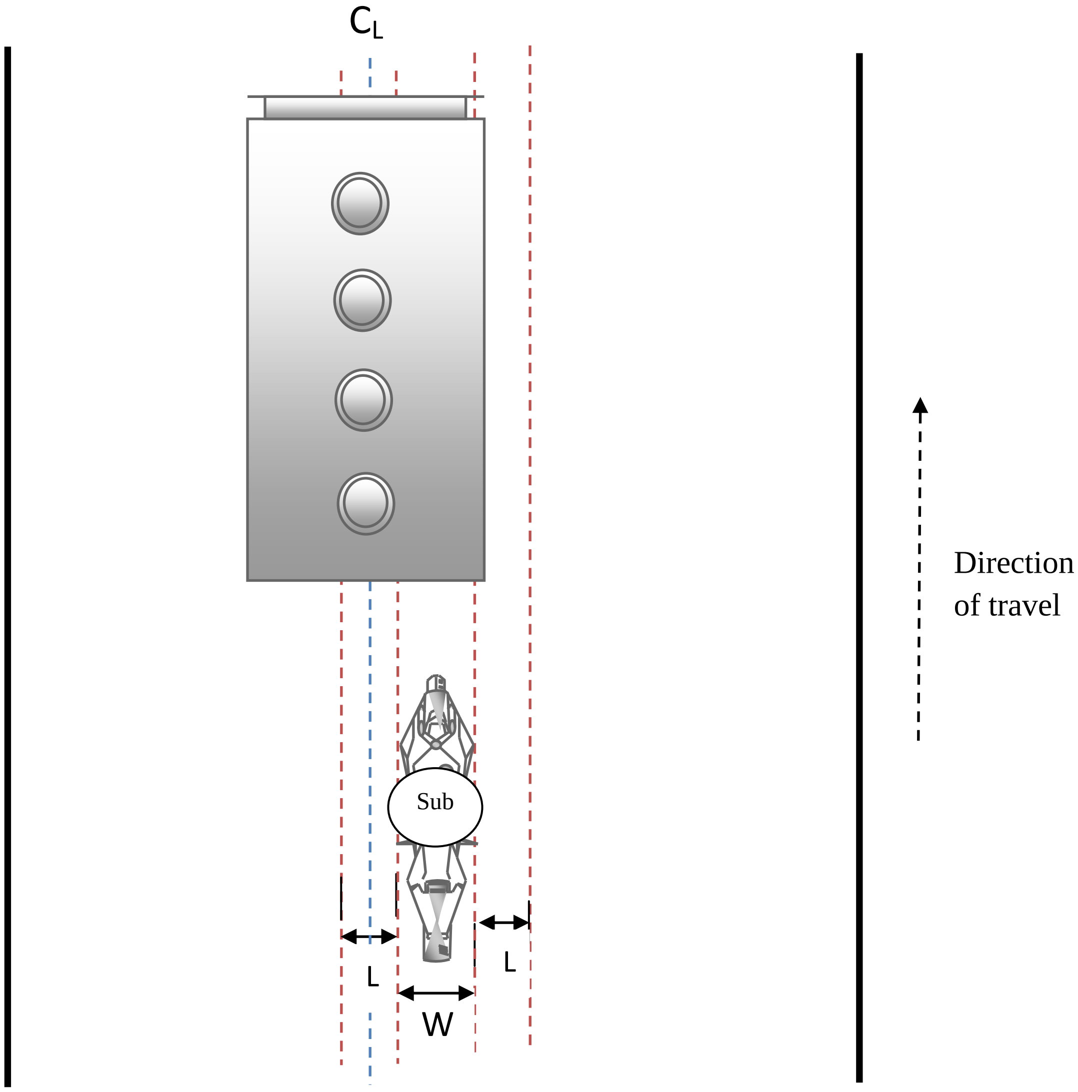


Figure 3.3 (a): Subject vehicle is motorcycle and front vehicle is bus

From figure 3.3 (a) it is found that the centerline of bus (C_L) is within the stretch of (W+2L) where, W is the width of motorcycle and L represents lateral gap on both side of motorcycle. So, it can be said that, bus can be counted as a front-direct vehicle for motorcycle.

Case 2

Subject is bus and there exists two front vehicles (two motorcycles)

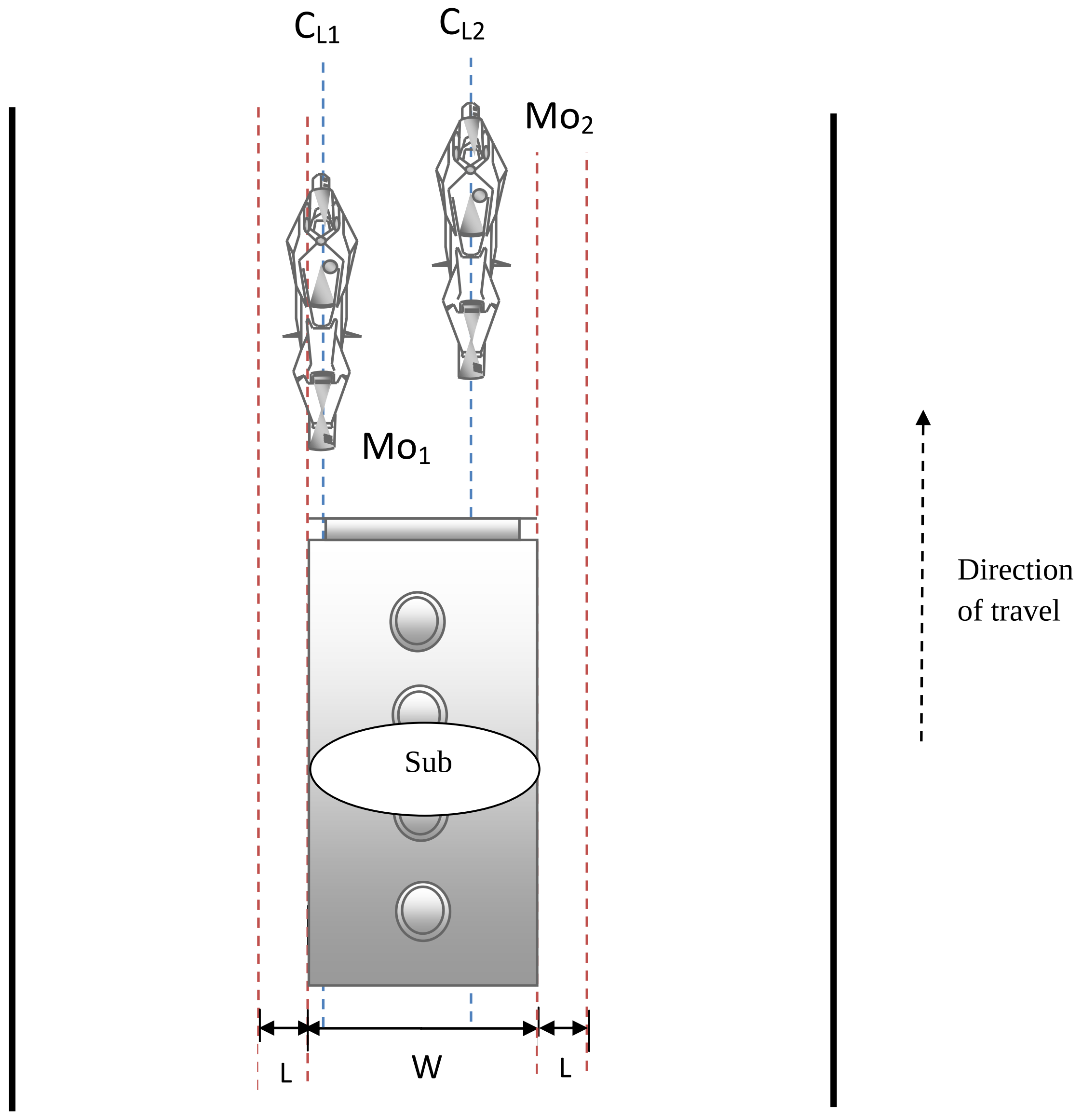


Figure 3.3 (b): Subject vehicle is bus with two motorcycles as front vehicles

From figure 3.3 (b) it is seen that the subject vehicle is bus and there exists two motorcycles in front of the subject vehicle. Moreover the centerline of the both motorcycle lies within the width of (W+2L), where W denotes the width of the bus and L accounts for the lateral gap on both side of bus. In such case, as the motorcycle on the left side (Mo_1) is closer to the bus (considering the distance rear bumper of the motorcycle to the front bumper of the bus), this motorcycle will be selected as the front-direct vehicle. The speed of the motorcycles have not been considered in this selection process as the selection is based on the instantaneous position of the vehicles, not their speed or type.

Case 3

Subject is car and front vehicle is motorcycle

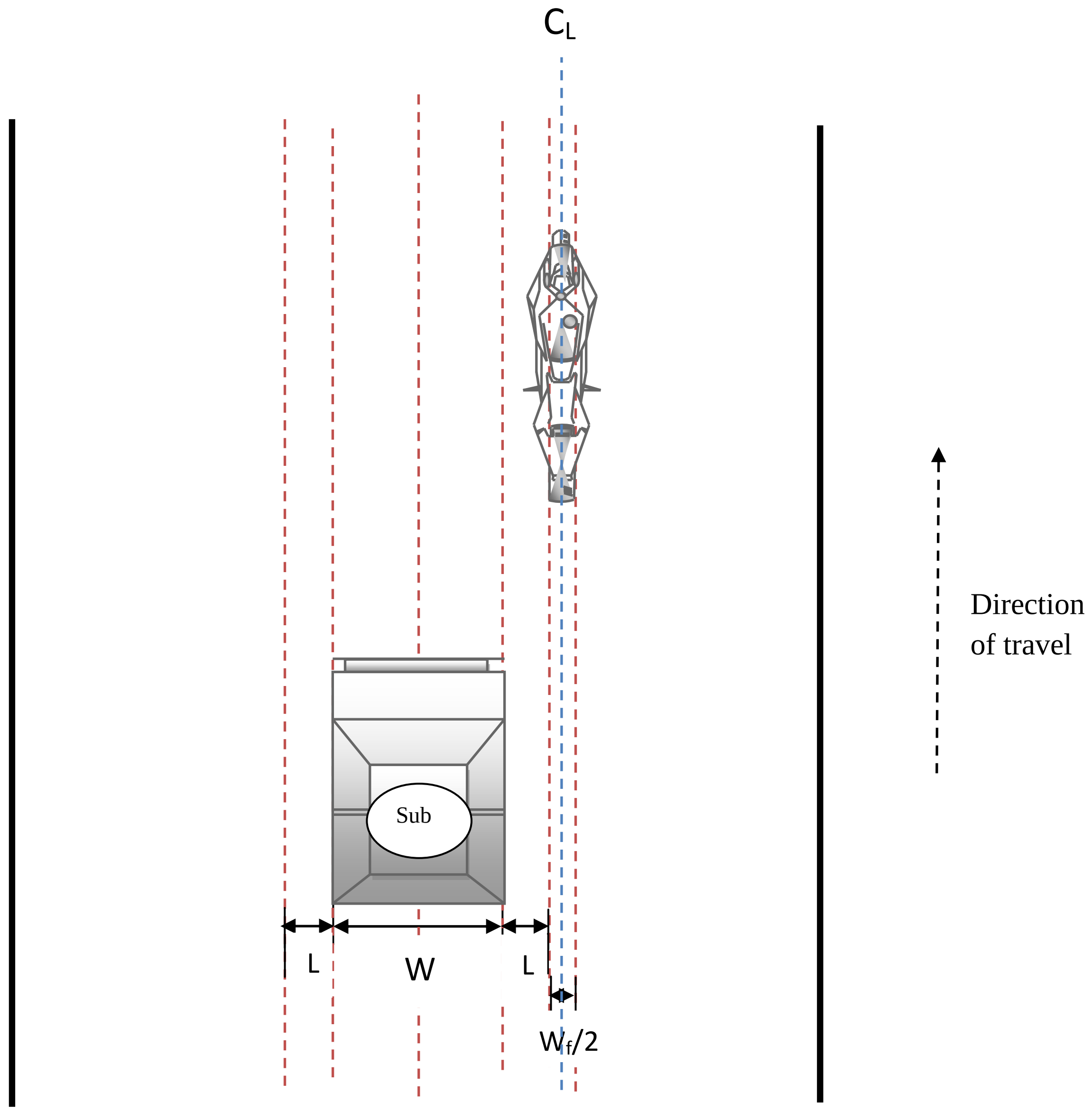


Figure 3.3 (c): Subject vehicle is car and front vehicle is motorcycle

In figure 3.3 (c) it is noticed that there is a motorcycle ahead of the subject vehicle (car). The centerline of the motorcycle is not within the range of (W+2L), where W is the width of the car and L is the lateral gap on both sides of the car. For this reason, the motorcycle will not be treated as the front-direct vehicle. Hence, the extended search width has been used which is dependent on the width of the front vehicle under consideration. It is seen that the motorcycle is on the right side of the car. Therefore, the extended search width will start from the right edge of the initial search area width (W+2L). The extended with is equal to $W_f/2$. Where W_f is the width of the front vehicle (here it is motorcycle). As the centerline of the motorcycle is within the range of (W+2L) and (W+2L+W_f/2 (right)), the motorcycle will be chosen as the front-right vehicle in this case.

Case 4

Subject is car and front vehicle is bus

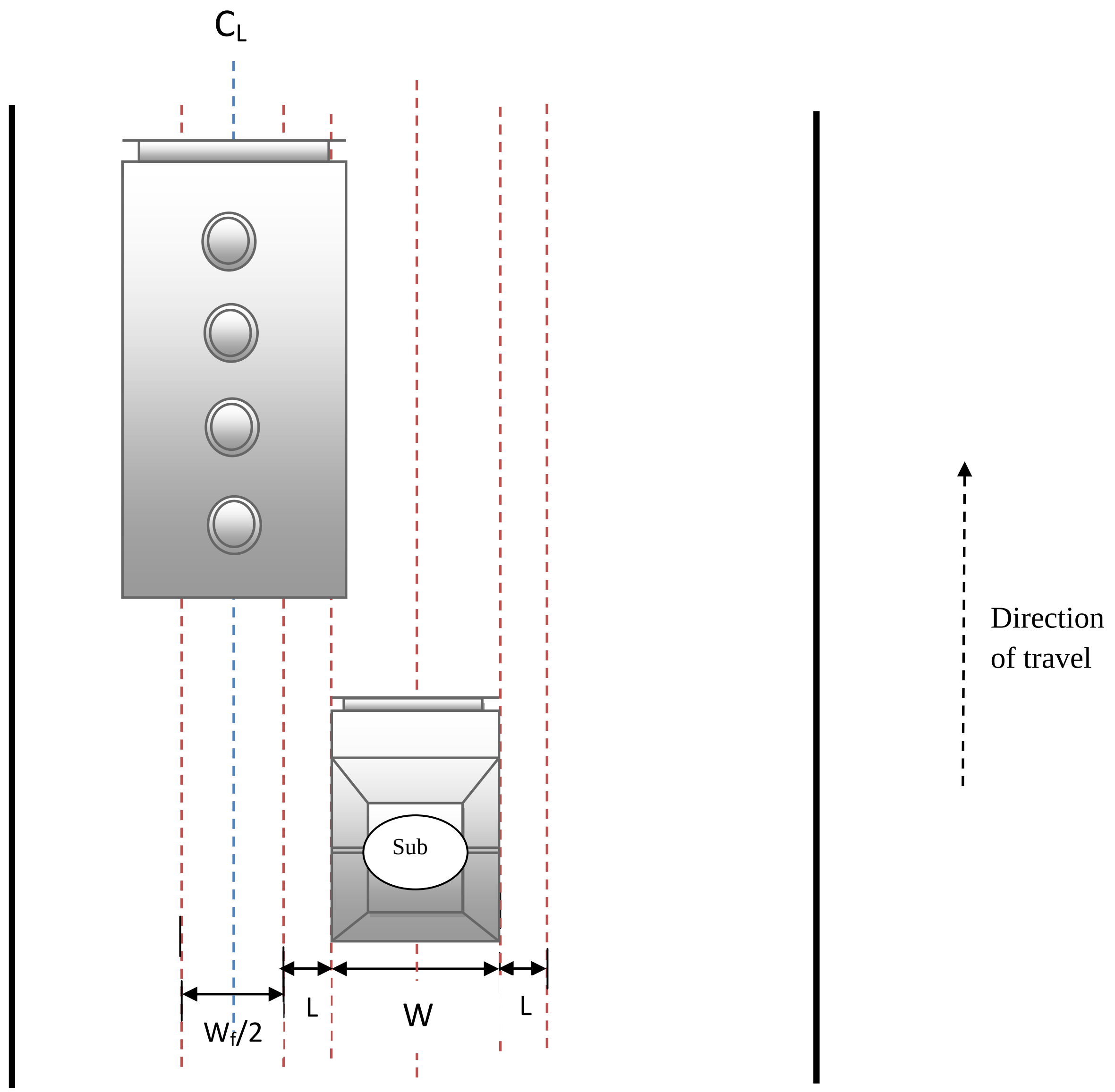


Figure 3.3 (d): Subject vehicle is car and front vehicle is bus

Case 4 is similar to case 3 except the front vehicle is bus instead of motorcycle. From figure 3.3 (d) it is found that the centerline of the bus is outside the range (W+2L), where W is the width of car and L is the lateral gap on both side of it. Therefore the bus can not be regarded as front-direct vehicle. Hence the further check comes into action. The centerline of the bus later has been checked with the extended search area width ($W+2L+W_f/2$ (left)), where W_f is the width of the front vehicle (bus). It has been found that the centerline of the bus lies within the range of (W+2L) and ($W+2L+W_f/2$). Therefore the bus will be selected as the front-left vehicle in this case.

This thesis will eventually focus the effect of all front vehicles on the acceleration/deceleration behavior of subject vehicle instead of one front vehicle. But in addition, a flowchart is shown in figure 3.5 to identify the critical front vehicle (or lead vehicle) in case more one than one front vehicle is present.

The subject vehicle driver evaluates at a specific time (t) whether he/she can maintain safe distance with the lead vehicle after decelerating at a normal deceleration rate for a period of time (δt).

Free flow headway or $h_{freeflow}$ = Distance between vehicles = (distance that can be travelled by the subject vehicle applying normal deceleration for a time δt) + (safe distance between the vehicles)

If the current longitudinal headway (at time t) becomes greater than $h_{freeflow}$, then the subject vehicle will be in the free flow regime (at least for this time step). The headway will be evaluated for the successive time steps as well.

Safe distance may be considered as the longitudinal gap between vehicles (if any front vehicle exists) which is dependent on vehicle characteristics. It is depicted in figure 3.4 and 3.5.

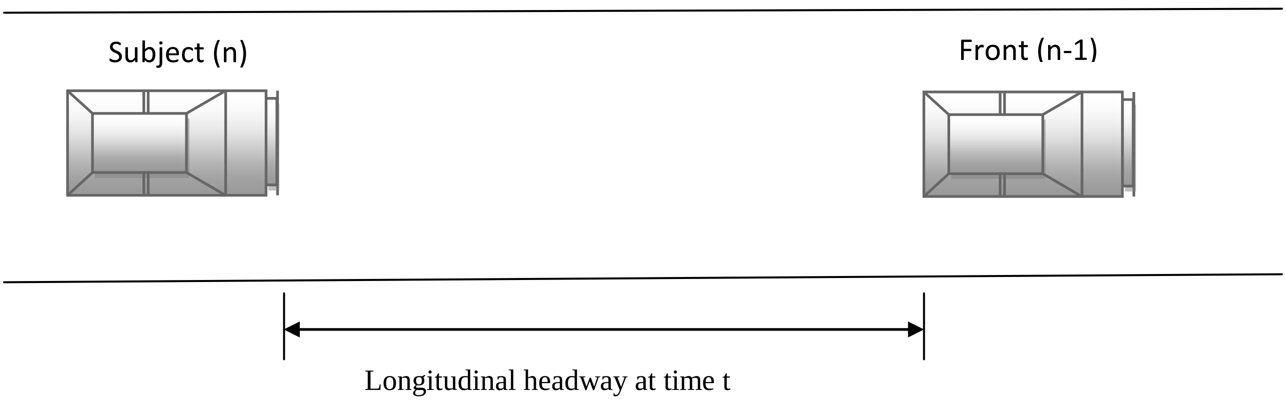


Figure 3.4: Position of lead and subject vehicle (follower) at time t

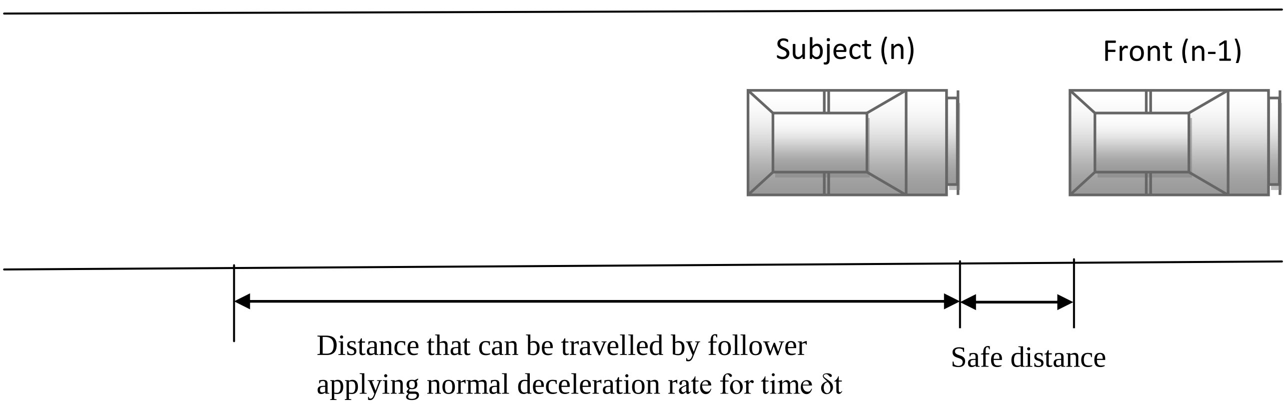


Figure 3.5: Position of the lead and subject vehicle (follower) at time (t+δt) assumed by the subject vehicle driver at time t

3.4.2.2 Flow-chart for identification of lead vehicle

The flow chart for identification of lead vehicle is depicted in figure 3.6

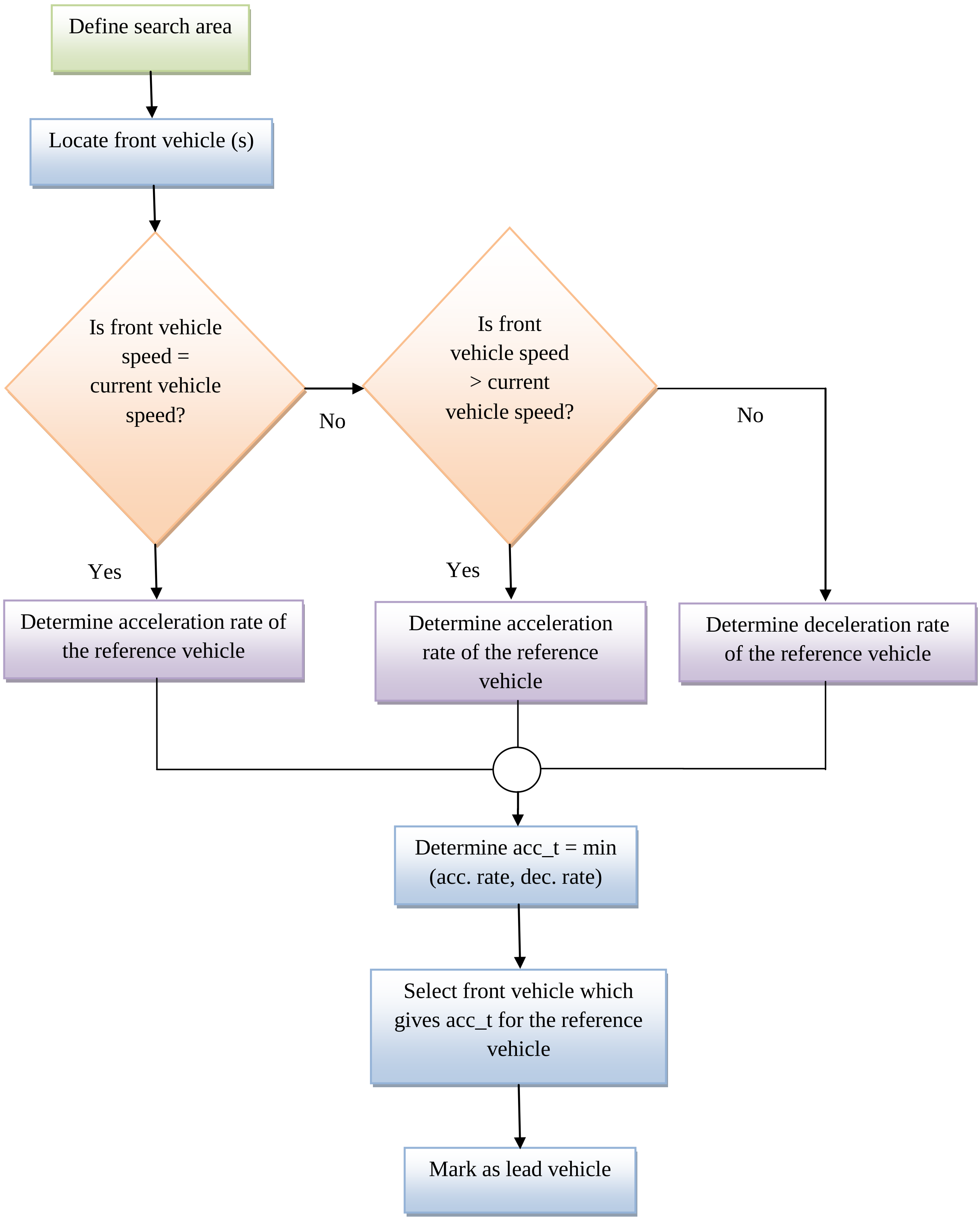


Figure 3.6: Flow chart for identification of lead vehicle

If in any time step the longitudinal headway becomes less than $h_{freeflow}$, the subject vehicle will enter in **car-following regime**.

There may be two cases in car-following state depending on the speed of the lead vehicle.

Case 1: If in any time instant the speed of the lead vehicle becomes zero or very close to zero (e.g. <5mph) as perceived by the subject vehicle driver (for application of emergency brake or any deceleration by the leader), then the subject vehicle will respond by applying deceleration (limited by the maximum deceleration rate) for a period of time to come to a stop or nearly so. ***Critical non-collision*** criteria will be satisfied by the subject vehicle. The illustration is provided at a later stage. Figure 3.7 and 3.8 will also depict the critical non-collision distance used to define this feature.

Case 2: If in any time instant the speed of the lead vehicle is not zero (perceived by the subject vehicle driver), the subject vehicle will accelerate or decelerate depending on the maneuver of the lead vehicle. ***Non-collision*** criteria will be satisfied by the following vehicle. Illustration of non-collision criteria is provided later. Non-collision distance is depicted in figure 3.9 and 3.10.

Governing Acc/Dec (from flow-chart)

Governing acceleration or deceleration rate is important in determining the lead vehicle in car-following regime and the maneuver of the subject vehicle depends on it as well.

Governing Acceleration*:* The acceleration rates of the reference vehicle for the next time step in response to the acceleration of the lead vehicle contenders are collected (both from modified stimulus-response model and from non-collision criteria). Among the acceleration rates the minimum acceleration rate will be considered as governing acceleration rate.

Governing Deceleration*:* The deceleration rates of the reference vehicle for the next time step in response to the deceleration of the lead vehicle contenders are collected (both from modified stimulus-response model and from non-collision criteria). Among the deceleration rates the maximum deceleration rate will be considered as governing deceleration rate.

Critical non-collision criteria (When the leader speed is zero or very close to zero; say <5mph)

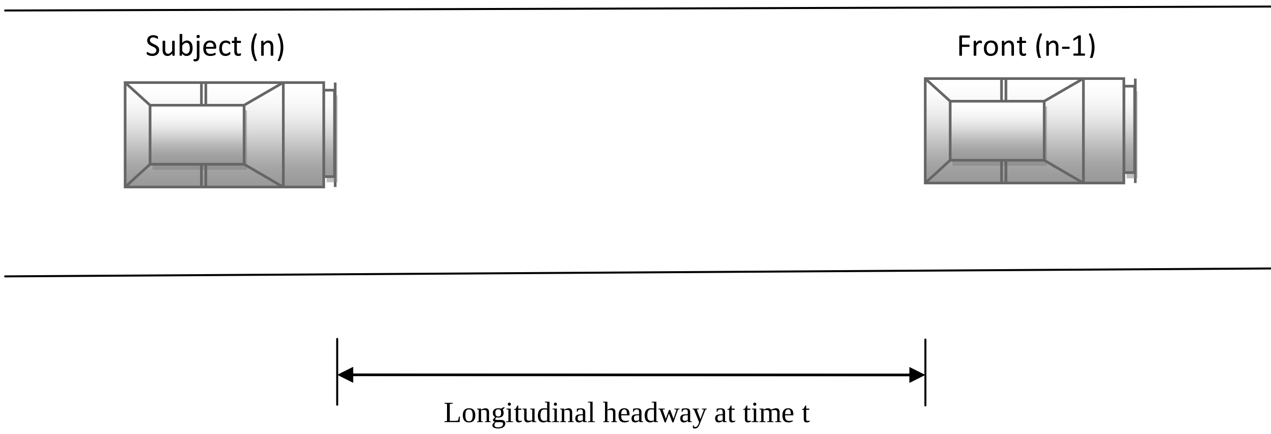


Figure 3.7: Position of lead and subject vehicle (follower) at time t

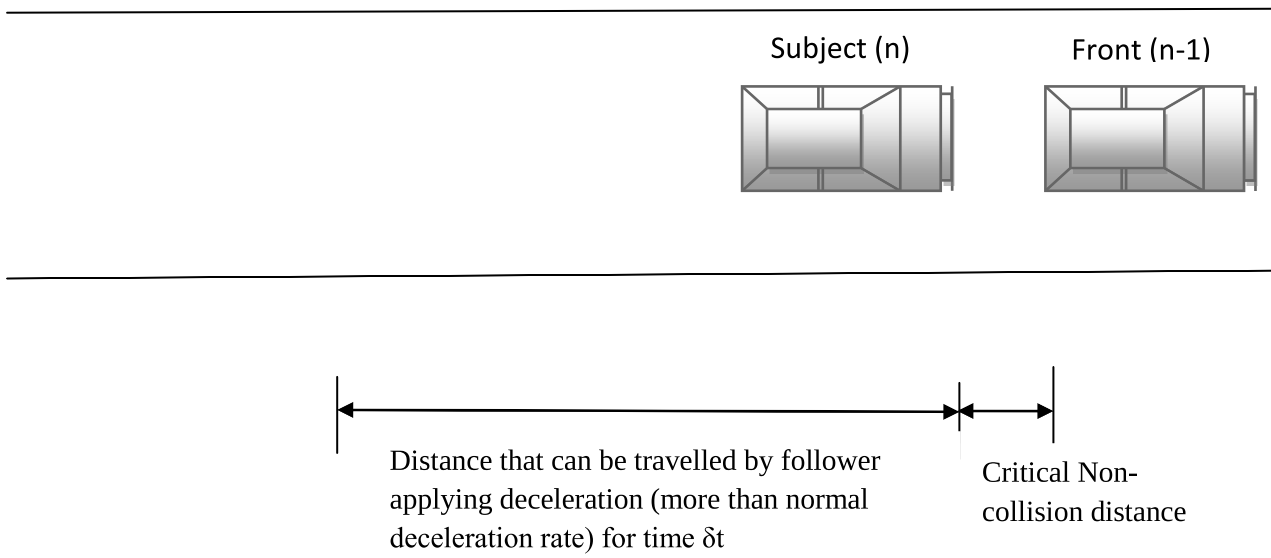


Figure 3.8: Position of the lead and subject vehicle (follower) at time (t+δt) estimated by the subject vehicle driver at time t

Non-collision Criteria (when the leader is speed is not zero)

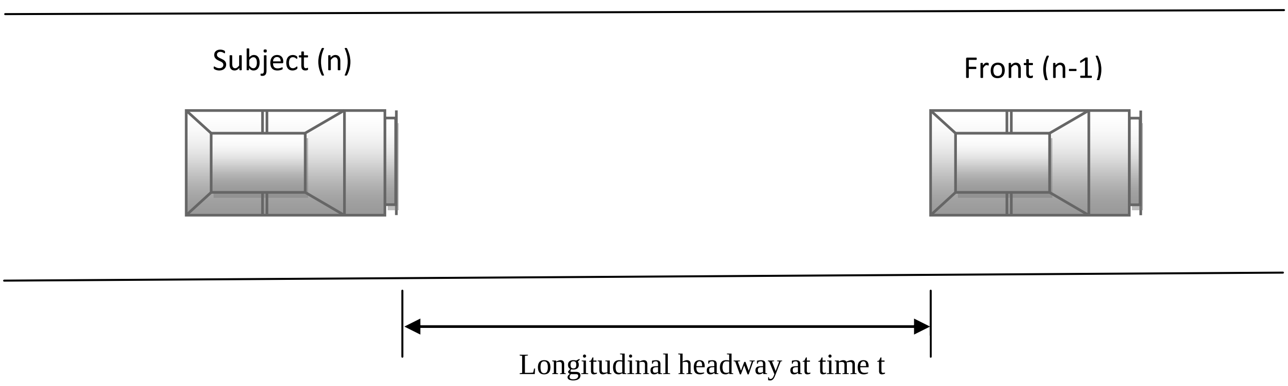


Figure 3.9: Position of lead and subject vehicle (follower) at time t

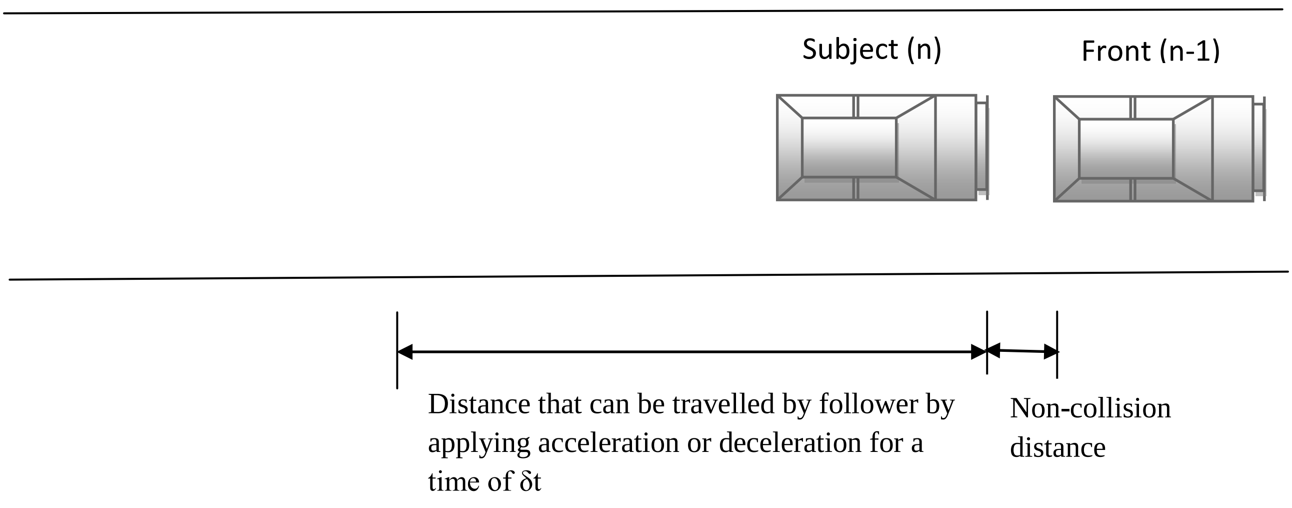


Figure 3.10: Position of the lead and subject vehicle (follower) at time (t+δt) estimated by the subject vehicle driver at time t

3.4.3 Data Requirement for Acceleration Model (for Longitudinal Movement)

A detailed explanation of the data required for the acceleration model is provided in table 3.1.

Table 3.1: Required data to be collected for thesis

Terms	**Illustration**	**Methodology for collection**	**Methodology for application in simulator**
Normal deceleration rate	The deceleration rate used to smoothly slow down a vehicle in non-emergency situation (free flow and car-following) and to compute normal stopping distance required for responding to a downstream event (e.g. traffic signal, incident and exit)	From using value collected by Hoque (1994) (The next line has been erased)	Setting equation of motion where the current speed and the final speed both are non-zero
Desired speed	The speed the subject vehicle driver wants to maintain in free flow condition; may be bounded by segment speed limit, road condition, driver aggressiveness and environmental factors	Obtained from field data, especially when traffic flow is minimum	Using a fixed value for a particular vehicle type in the simulation library
Non-collision distance	The longitudinal gap maintained by a following vehicle while following a leader (the leader speed is non-zero); depends on vehicle pair	From field data; set a range of value for a particular vehicle pair (e.g. the leader is bus and a follower is a car or reverse) depending on the speed of the lead and following vehicle	Using the following equation of motion, $v^2 = u^2 - 2*a*(s-h_{nc})$
Critical non-collision distance (can also be termed as stopped longitudinal gap)	The longitudinal gap maintained by a following vehicle when the subject vehicle speed is zero (or very close to zero); depends on vehicle pair	From field data; set fixed value for a particular vehicle pair (e.g. leader is rickshaw and follower is car or reverse)	Using fixed value for a particular vehicle pair (e.g.the leader is rickshaw and the follower is car or reverse)

Free-flow distance	Distance that can be travelled by the subject vehicle applying normal deceleration for a time period satisfying safe distance between the vehicles	From field data when traffic flow is minimum	Using equation to determine distance that can be travelled by the subject vehicle applying normal deceleration for a time period satisfying safe distance between the vehicles $h_{free\text{-}flow}$=ut+0.5*a*t^2 where, t is the assumed time which has not been fixed yet
Safe distance	Assumed distance used in determining free-flow distance	From field data, especially when traffic flow is minimum (free flow condition)	Greater than non-collision distance; the increment over NC distance yet to be determined

3.5 Summary

The tentatively selected model structure is relatively simple in nature. In this chapter a flow chart has been shown to demonstrate the acceleration behavior in different driving regime. Another flow chart has illustrated how a driver can identify the potential lead vehicle from a number of front vehicles only. But it is fact that, there may be the effect of all the front vehicles on the acceleration maneuver of the subject vehicle in different extent and showing their effect is the main objective of this thesis. It should also be noted that this research will highlight on car-following acceleration only, not acceleration on free-flow or lane changing situations.

Chapter 4

Data Collection

4.1 General

Data is mandatory for any type of research or study. Type, quality and quantity, sensitivity and data collection method entirely depends on the purpose of the research and economic feasibility associated with the research. A suitable data collection plan is therefore is of utmost important to conduct a study. In this thesis data will be collected to develop acceleration model and calibration of the developed model. In the following subsections data requirement, data collection methodology and other relevant features related to data collection will be discussed.

4.2 Secondary Data

Secondary data is used to supplement primary data when necessary. Sometimes this data becomes useful to check the validity of the primary data. In some cases secondary data is used entirely if primary data is unobtainable. In this study the secondary data have been taken from the thesis of Imran (2007). The data contains the position, speed and acceleration of vehicles with a specific time interval. The data were collected from Banglamotor Intersection of Mirpur Road of Dhaka City. The data was mainly collected to formulate car-following model using fuzzy logic model as described in chapter 2.

The data will be used to calibrate the non-linear GM Model (stimulus-response model model) and the result will be checked with the calibration result using primary data. Primary data description and collection methodology are illustrated in the next subsections.

4.3 Primary Data

The primary data for this study contains disaggregate and aggregate data. The disaggregate data includes GPS and video data while the aggregate data contains video data only. Disaggregate data will be used for acceleration model development and calibration purpose. Aggregate data will also be used for aggregate calibration of the developed acceleration model.

In the GPS data, second-by-second trajectory of the vehicles will be stored for identifying longitudinal and lateral movement of vehicles as well as 2D movement (combination of longitudinal and lateral movement). The data will later be processed to identify position, speed and acceleration of vehicles which are the input of proposed acceleration model for heterogeneous traffic.

The video data, collected by video camera as video recordings, will consist of the actual movement of traffic. As the data itself is realistic, it can be an excellent source for event identification like lateral movement in terms of overtaking, turning, lane-changing, merging, etc. the data can also provide sufficient insight for acceleration decisions like identifying the stimulus for acceleration or deceleration. The data can later be combined with GPS data to supplement the disaggregate data or cross examined with GPS data to check the actual movement with movement found from GPS data. The video data will also be used to determine density of traffic of a road section which is an important parameter of car-following model.

4.4 Methodology for Primary Data Collection

Primary data are required for model development and calibration. Before primary data collection a data collection plan is prepared which includes the following features.

4.4.1 Data Collection Location

Some criteria had to be selected depending on the purpose of the data. Here for primary data (video and GPS data) the locations were chosen in such a way that a perfect synchronization of data collection is possible for future combination or necessary checking. Therefore, both types of data were collected in the same road network at the same time. Also the sites suitable for both types of data had to be considered. As the GPS data had to be collected periodically, a specific route was identified and as the video data was decided to be collected by video camera, a common network was inevitable. The road network was therefore would consist of both the route or road track and the video data collection spot.

4.4.2 Data Collection Method

Video data were to be collected continuously and therefore required video recording for a specific period. A mounted place would be ideal for video camera and its maneuver. The GPS data was required to be collected continuously along a specific route and therefore some test vehicles equipped with GPS devices was selected as GPS data collection mode.

4.5 Site Selection for Primary Data Collection

4.5.1 Site Selection Criteria

The criteria for selecting locations for primary data collection are as follows,

Raised platform for placing camera: the site should contain a raised space like foot over-bridge to place the video camera.

Continuous movement of vehicle: there should be continuous movement in the site with a reasonable speed.

Straight portion of road: the road section should be free from any bend or curve portion so that flow for a reasonably straight road length can be obtained.

Minimal side friction: as the side friction hampers the natural movement of traffic the location should be free from it (or the side friction should be minimum if cannot be avoided).

Avoidance of large commercial vehicles: image processing software will be used for vehicle counting which works on the basis of only frontal view of traffic and therefore the large vehicle operating road section is not expected (as it obstructs the frontal view of small sized vehicles like private car and auto-rickshaw).

4.5.2 Reconnaissance Survey

In order to select suitable site for data collection, after fixing criteria a reconnaissance survey was conducted. A number of preliminary locations were identified beforehand and short video and screenshots were taken to get detailed information for subsequent final choice.

4.5.3 Final Selection

The candidate locations identified by the reconnaissance survey were thoroughly checked against each criterion and finally two locations were confirmed for video data collection. Location one is Kalabagan and location two is Shukrabad. The video cameras were mounted on over bridges in these two sites. Figure 4.1 shows the camera location on Kalabagan over bridge (near Kalabagan Intersection) with the direction of both camera and traffic. A snapshot of traffic approaching Kalabagan from Asad Gate intersection is presented in figure 4.2. The opposite directional traffic of this location (approaching Kalabagan from New Market) is shown in figure 4.3.

It can be seen from Figure 4.1 that there are two video cameras for capturing two opposite directional traffic. The camera direction is naturally the opposite of traffic direction. Camera 1 captures the traffic coming from Asad Gate and moving towards

New Market (these locations are not present in figure 4.1). Camera 2 captures the traffic flowing at opposite direction (from New Market to Asad Gate).

Figure 4.1: Kalabagan over bridge (with camera and traffic direction) (Source: Google Earth)

Figure 4.2: Traffic approaching at Kalabagan Intersection from Asad Gate

Figure 4.3: Traffic approaching Kalabagan Intersection from New Market

The second data collection site is Shukrabad and only one camera has been used in this location (figure 4.4). The camera is capturing the traffic from Asad Gate to New Market direction. In figure 4.5 the traffic approaching Shukrabad intersection from Asad Gate is exhibited.

Figure 4.4: Shukrabad over bridge (with camera and traffic direction) (Source: Google Earth)

Figure 4.5: Traffic approaching Shukrabad Intersection from Asad Gate

The GPS data were collected along with the video data for disaggregate calibration. Total five vehicles were run along a specified route congruent with video data location site. The route is shown in figure 4.6. Some points on the road are also shown in the picture to mark that the road network coordinates were obtained from GPS data as well.

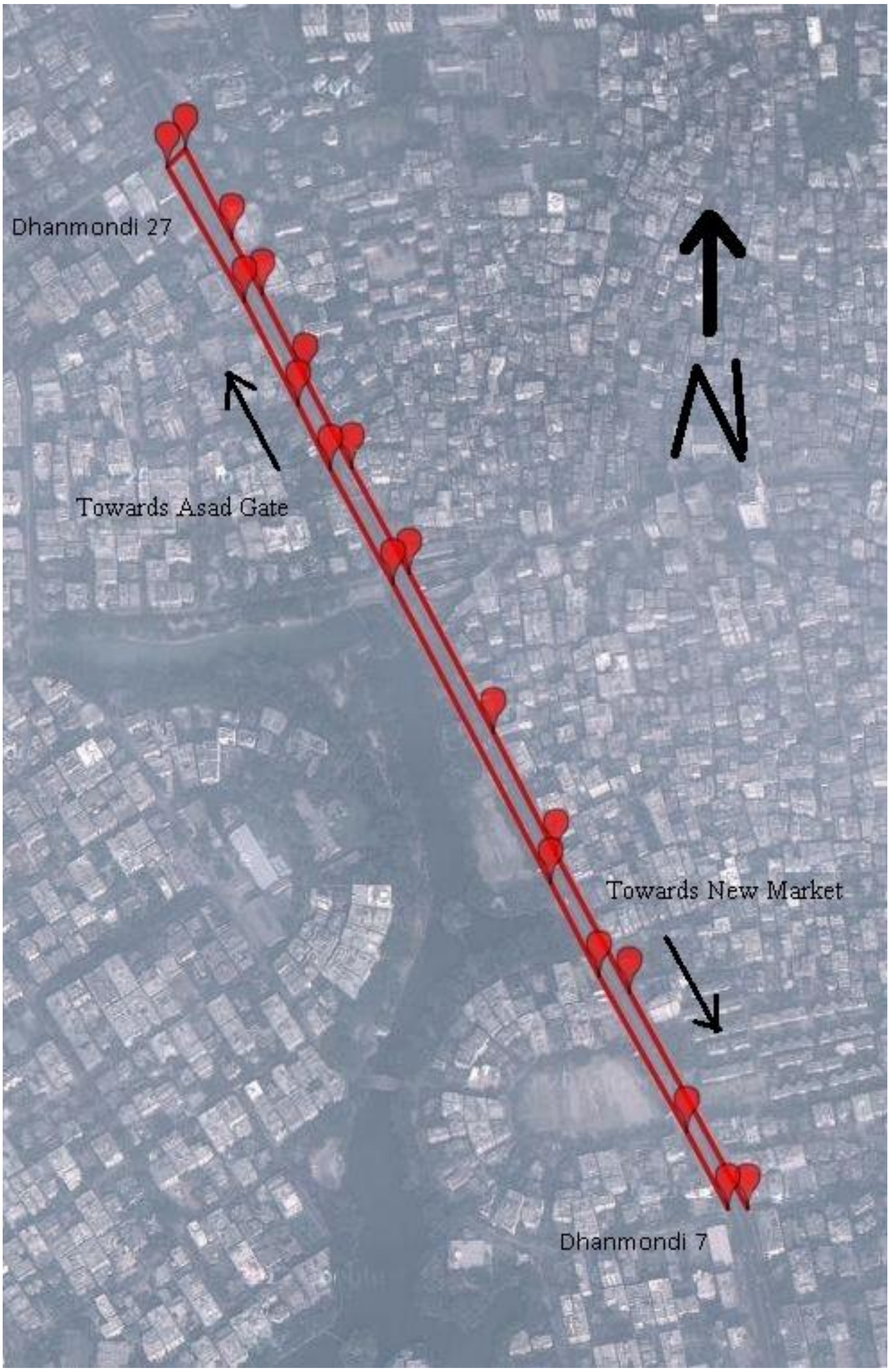


Figure 4.6: Route for GPS data collection (with data points)

4.6 Collection of Primary Data

It has been mentioned that the primary data consists of video data and GPS data.

4.6.1 Video Data

The video data were collected as video recording by video camera placed at two foot over bridges in Mirpur road of Dhaka city. The over bridges are at Kalabagan and Shukrabad as mentioned earlier. The video data were collected for about 1 hour duration continuously and the camera was set at a particular position and specific viewing angle to capture the front view of all the vehicles passing the site (over bridge).

4.6.2 Auxiliary Data (GPS Data)

There were five test vehicles equipped with high precision GPS devices. Four types of vehicles were used; two private cars, one microbus, one CNG auto-rickshaw and one motorcycle. The vehicles were run along pre-specified tracks of Mirpur road for approximately one hour (figure 4.3). The raw data mainly consists of the position of vehicles and the points are taken with one second interval. Some other information is also present in the data log.

4.7 Difficulties in Primary Data Collection

There were some obstacles before and during primary data collection. The main difficulties during collection of video data at both locations are are as follows:

Overall

- Perfect site for data collection (all cretiria could not be met)

Site specific

- Mid-section of the road not long enough to capture the acceleration of the traffic in full scale
- Road bend to hinder the smooth longitudinal movement of traffic
- Occassional view obstruction of the smaller vehicle close to a large vehicle (as overbridges are not high enough to capture large platton of traffic by the video camera)
- Vibration on the overbridge (due to pedestrian movement) affecting the video clip
- Occasional side friction hampering traffic flow

4.8 Summary

In this chapter a proper data collection methodology has been explained. Site selection, data collection technique, requirement and use of data have been described as well. It has been found that there are some difficulties associated with data collection which has been resolved later. It is evident that data collection plan is as important as the data itself. Therefore the whole methodology for data collection was devised with proper discretion and data was collected using the appropriate procedure.

Chapter 5

Data Analysis and Model Development

5.1 General

Data analysis is one of the most important parts of this thesis to show the way of how the data has been processed and used to get the ultimate result. Therefore it is necessary to properly demonstrate the process and explain every terms and steps associated with the analysis. In this chapter the whole process starting from data processing to model development will be discussed.

5.2 Data Analysis

5.2.1 Secondary Data

The secondary data was taken from Imran's thesis as mentioned earlier. The data contains the video recording of a traffic flow (of approximately 45 minutes) at Bangla Motor intersection and more specifically the approach of Sheraton intersection to Bangla Motor intersection. The raw data was processed by the author later to get local coordinates which was used to find position, speed and acceleration of the vehicles. The author used Auto Rickshaw as the reference vehicle for his research.

The data has been used by the author of this thesis for calibration purpose of the non-linear GM Model (car-following model) and car-following parameters have been estimated as well. Time vs speed, time vs acceleration were also drawn to show the effect of the lead vehicle on the following vehicle.

5.2.2 Effect of Reaction Time

Reaction time is the time duration between drivers' recognition of a stimulus (speeding or slowing of front vehicle, increasing or lessening of gap with the front vehicles, etc.) and execution of acceleration or deceleration operation according to the stimulus. Reaction time varies from driver to driver based on age, gender, experience of driving (vehicle-mile), physical and mental condition (fatigue, alcohol effect) and also on roadway, traffic and weather conditions. Therefore reaction time is an important issue in modeling acceleration behavior of drivers.

The secondary data has been estimated using different reaction times (e.g. 0, 0.25, 0.5, 0.75 and 1 second). The calibration result for selection of reaction time using the secondary data is provided from table A.1 to A.5 (appendix A).

5.2.3 Effect of Candidate Variables

Later a number the effect of different candidate variables (which affect acceleration/deceleration decision) has been demonstrated using a number of curves). The data points have been taken for a particular leader-follower combination to get an idea of what the relation between acceleration/deceleration and the influencing variables (explained at section 5.3.2) look like. This also makes the curves quite simple. In case of a traffic stream no such pattern can be identified due to vast heterogeneity in type of vehicle and difference in drivers' decision making (reaction time, driver demographic factors dependent) and implementing process (actual execution also depends on driver demographics and reaction time).

The sample curves are depicted from figure A.1 to A.6 in the appendix section (Appendix A).

It must be noted that the secondary data has been used only to show the effect of reaction time. No acceleration (or deceleration) models have been developed using secondary data.

5.2.4 Primary Data

The raw primary GPS data contains

(1) Vehicle ID
(2) Time
(3) Latitude
(4) Longitude
(5) Mode of GPS device (Autonomous and DGPS)

Some other information is also stored but may not be required for the purpose of the thesis and therefore have not mentioned here. When the latitude and longitude data are given as input in 'GPS Visualizer', this software gives the trajectory of the vehicles which were equipped with GPS devices earlier.

The raw video recording contains no written data itself and therefore has been analyzed extraction of useful information. The video was analyzed by image processing software named 'TRAZER'. The software was used to obtain the following parameters,

(1) Vehicle count (later transformed to flow)
(2) Vehicle classification
(3) Average velocity
(4) Average occupancy
(5) Vehicle trajectory

In the following section detailed data about the vehicle composition and vehicle combination has been provided.

5.2.4.1 Vehicle composition

From the video data 2000 vehicles have been found in aggregate. The classified vehicle count is presented in table 5.1.

Table 5.1: Vehicle composition in the traffic stream

Major Class	Subclass	Number	Percentage
Light Motor Vehicle (LMV)	Private Car (C)	969	48.45
	SUV (S)	107	5.35
	Microbus (M)	142	7.10
	Pickup (P)	10	0.50
	Human hauler/Utility vehicle (H)	25	1.25
Three-wheeler (3W)	CNG Auto-rickshaw (A)	229	11.45
Heavy Motor Vehicle (HMV)	Bus (B)	160	8.00
	Truck (T)	5	0.25
Two-wheeler (2W)	Motorcycle (Mo)	244	12.20
	Bicycle (Bc)	45	2.25
	Cycle Rickshaw (R)	64	3.20
	Total	**2000**	100

From table 5.1 it is evident that the traffic stream mostly consists of private cars (48.45%) followed by motorcycle (12.20%). CNG autorickshaw also has a fairly good percentage. The percentage of bus and microbus are close and considerable. Based on the traffic composition the majority of the front-subject vehicle combinations consist of the following nine combinations (subject vehicle type comes first).

1. Car-Car (C-C)
2. Motorcycle-Motorcycle (Mo-Mo)
3. CNG Autorickshaw-CNG Autorickshaw (A-A)
4. Bus-Bus (B-B)
5. Microbus-Microbus (M-M)
6. Car-Motorcycle (C-Mo)
7. Motorcycle-Car (Mo-C)
8. Car-CNG Autorickshaw (C-A)
9. CNG Autorickshaw-Car (A-C)

In table 5.2, the number of aforementioned vehicle combination is provided. It must be noted that, in this thesis, the subject vehicle may have three front vehicles at the same time. In calculating the number of combinations, the subject vehicle with at least one of the front vehicles of the mentioned type has been counted. For example, if a car has three different types of front vehicles at the same time (e.g. motorcycle, microbus and car), it has actually been counted as three combinations (car-motorcycle, car-microbus and car-car). As other types of vehicles are not so abundant in the traffic stream, the remaining possible combinations have been omitted.

Table 5.2: Different vehicle combinations in the traffic stream

Vehicle Combination	Counts
Car-Car (C-C)	343
Motorcycle-Motorcycle (Mo-Mo)	34
CNG Autorickshaw-CNG Autorickshaw (A-A)	5
Car-Motorcycle (C-Mo)	82
Motorcycle-Car (Mo-C)	30
Car-CNG Autorickshaw (C-A)	99
CNG Autorickshaw-Car (A-C)	13
CNG Autorickshaw-Motorcycle (A-Mo)	5
Motorcycle-CNG Autorickshaw (Mo-A)	6

It can be seen from table 5.2 that the number of counts of Car-Car combination is maximum and much more than the second placed combination (Car-CNG Autorickshaw) as expected. Although the number of Motorcycle is more than CNG-Autorickshaw, the number of Car- CNG Autorickshaw combination is greater than that of Car- Motorcycle combination. The reason may be that, the motorcycle drivers have little patience to stay in the present direction and therefore changes direction rapidly. It is alo seen that Motorcycle-Car combination is less than Car-Motorcycle combination. The lesser number of motorcycles in the traffic stream with respect to car is a good reason for this imbalance. But the spiral movement of motorcycle (unlikely to stay behind a car) may be also a reasonable cause behind this statistics. In the video it was seen that, motorcycles sometimes ran as a platoon and this feature is reflected in the fairly good number of Motorcycle-Motorcycle combination.

The trajectory data found from TRAZER gives the global coordinate of the vehicles on a frame basis which was later used to find position, lateral and longitudinal speed and lateral and longitudinal acceleration of each vehicle using MATLAB' code. The whole data processing using MATLAB is described in figure 5.1.

Step 1: Read trajectory data file

Step 2: Read vehicle type data and group of multiple ids of a vehicle data

Step 3: Discard all the invalid vehicle ids from data file

Step 4: Group together all the ids of a vehicle (if any)

(Consider only forward movement)

Step 5: Convert frame ids to time and distribute to predefined interval

Step 6: Smooth X and Y trajectory data for each vehicle using 5th order polynomial fit

Step 7: Place smoothed X and Y trajectory data in the predefined time interval (done in step 5)

Step 8: Determine speed and acceleration from smoothed X and Y coordinate and time interval (using equation of physics)

Step 9: Smooth speed and acceleration of each vehicle using 5th order polynomial fit

Step 10: Discard frame id with only one vehicle

Step 11: Detect front vehicle for each vehicle and each time interval

Step 12: Determine vehicle speed and acceleration using step 1 to 9

Figure 5.1: Steps of variable generation from trajectory data using MATLAB

In TRAZER, the X and Y coordinates of the vehicles were defined as the midpoint of the front bumper line of vehicle, so the spacing was initially obtained as the front bumper to front bumper distance. The gap was then converted to clear spacing by using standard dimension of each vehicle class.

In MATLAB, the time headway (time equivalent of front relative spacing) has been considered as the following.

Minimum time headway > 0

Maximum time headway = 3 second

In other words,

Zero < time headway < 3 second

The time headway was used to search for front vehicles. The search area width demonstrated in figure 3.2 has been used while detecting front vehicles using MATLAB variable generation code. After the generation of the input variables for acceleration and deceleration models, effort has been given to formulate models.

It is to be mentioned that, the maximum value of acceleration and deceleration has been kept to 5 meter per square second and 6 meter per square second respectively in order to get the best possible model estimation result from the generated input variables data.

The next section will give detailed technique about the formation of acceleration models from generated input variables.

5.3 Model Formulation

In order to get suitable models for acceleration and deceleration maneuver of the subject vehicle, the selection of suitable reaction time is important. The following section will briefly discuss the effect of reaction time on the modeling of acceleration behavior of drivers. Moreover, the selection procedure of appropriate reaction time for subsequent model formulation will be explained.

5.3.1 Effect of Reaction Time

As already mentioned in section 5.2.1 reaction time has considerable impact on the decision of drivers along with other variables (vehicle, road, traffic and driver properties), the selection of the reaction time will be a prerequisite for development of acceleration and deceleration models. The model used for testing the effect of reaction time is Modified GM Model (Gazis, 1961). The model form has been presented already in chapter 3. From a number of literatures it has been found that the reaction time is tested from 0 to 1.5 second in most cases (for example, Ahmed (1999) used reaction time of 0 and 1 second) and the actual value also varies usually in this range. In this thesis, reaction time has been tested for values of 0, 0.2 second and 0.5 second. Reaction time effect for higher time (like 1 second) could not be analyzed due to very small data size which affects the model result. It should also be noted that, due to difference in data size, adjusted R-square values were not comparable across model result for different reaction time.

Table 5.3 and table 5.4 represent the effect of reaction time on acceleration and deceleration maneuver of drivers respectively. The subject vehicle with its interaction with its front vehicles (front left, front direct and front direct) has been modeled separately. It has been seen that the best results (in terms of anticipated signs and t-stats) have been found when the reaction time is zero. The size of data may be an important factor for the model performance. It may also be due to the fact that, as the road is an urban road and vehicles operating all the time with a reasonable density, the drivers are alert for most of the time and expect any unexpected event ahead at any time instant.

Table 5.3: Effect of reaction time on acceleration maneuver of drivers

Subject and front left vehicle pair (Reaction time is zero) No. of Observation= 2956 Adjusted R-square= 0.235		
Parameter	Value	t-stat
constant	2.15	14.8
Beta_subject speed	-2.51	-25.8
Beta_relative spacing	-0.0696	-1.56
(Reaction time is 0.2 second) No. of Observation= 1656 Adjusted R-square= 0.164		
Parameter	Value	t-stat
constant	0.80079	7.35
Beta_subject speed	-2.25	-13.6
Beta_relative spacing	-0.211	-2.02
(Reaction time is 0.5 second) No. of Observation= 1395 Adjusted R-square= 0.0797		
Parameter	Value	t-stat
constant	0	-0.19
Beta_subject speed	17.9	5.84
Beta_relative spacing	-0.576	-1.86

Table 5.4: Effect of reaction time on deceleration maneuvers of drivers

Subject and front left vehicle pair (Reaction time is zero) No. of Observation= 3002 Adjusted R-square= 0.224		
Parameter	Value	t-stat
constant	1.73	17.7
Beta_subject speed	-2.33	-25.5
Beta_relative spacing	-0.115	-2.53
(Reaction time is 0.2 second) No. of Observation= 1667 Adjusted R-square= 1.17		
Parameter	Value	t-stat
constant	0.812	6.89
Beta_subject speed	-2.28	-12.7
Beta_relative spacing	-0.206	-1.85
(Reaction time is 0.5 second) No. of Observation= 1402 Adjusted R-square= 0.974		
Parameter	Value	t-stat
constant	0	-0.70
Beta_subject speed	8.42	9.27
Beta_relative spacing	-0.10084	-0.54

The model estimation has been performed using statistical software STATA SE (Version 11). As the reaction time has been varying there is a considerable change in the number of observations as well. It is obvious that the number of observations is likely to diminish with increasing reaction time as there will be a time lag consideration while extraction of valid data for model estimation. For example if the reaction time is zero second, it means that there will be no time lag and all available vehicle pair data will be used.

It has been seen that the model results (both for acceleration and deceleration) are better in zero reaction time in terms of the adjusted R-squared value, the value of the coefficients and their t-stat values mainly due to greater number of observations. Therefore, for the consecutive analysis of acceleration and deceleration data, zero reaction time will be used.

5.3.2 Influencing Variables

There are a number of factors which substantially affect the acceleration or deceleration maneuver of drivers. All variables are not quantifiable but representable in some extent. The effect of the most crucial variables is described below. It must be noted that the following descriptions are not derived from the analysis of the data or the model result. Rater the illustrations are gathered from the observation of real time traffic movement on the site.

Type of front and subject vehicle

It is fact that the static and dynamic characteristics of vehicles differ from vehicles to vehicles according to vehicle class. Therefore the way of maneuvering vehicle is different. There is a significant difference between the acceleration maneuver of a car (motorized vehicle) and cycle-rickshaw (non-motorized vehicle). A car driver accelerates a particular way while another car is in front and it becomes different when a rickshaw appears in front of that car driver. Moreover, the presence of heavy vehicle in front affects the maneuverability of the driver. For instance, if a bus is in front of a car, the car driver becomes cautious for the size of its front vehicle and it affects the driving behavior. Sometimes it is also found that the car drivers (also motorized vehicle drivers) try to avoid a non-motorized vehicle in front and accelerates or decelerates to change its present direction.

Subject speed

The speed of the subject vehicle has its own effect on the acceleration it exerts even there is no influence of the front vehicle. It is seen that in most cases, the acceleration value of the vehicle is maximum after it starts from the stop condition and decreases gradually as the speed increases. In presence of the front vehicle, the subject vehicle tries to maintain at least equal speed of the front vehicle (overtaking not considered) and the acceleration rate varies accordingly.

Front relative speed

Any vehicle within the search area of the subject vehicle will have to some extent on the acceleration or deceleration decision on the driver of the subject vehicle. Relative speed (or the speed difference between the front and subject vehicle) acts as a stimulus and in response the subject vehicle driver changes acceleration rate. If the relative speed increases (increment of speed of the front vehicle), the subject vehicle also react by applying acceleration (increasing acceleration rate). On the other hand, when the relative speed decreases, the subject vehicle applies deceleration (reduces the acceleration rate) in compliance with the action of the front vehicle.

Relative spacing

Relative spacing refers to the longitudinal gap (gap along the direction of the road) between the front and subject vehicle. Relative spacing also acts as a visible stimulus and quickly perceivable by the subject vehicle driver. An increase of the space is reacted by the increment of the acceleration rate of the subject vehicle. Likewise, when the longitudinal gap is reduced, the subject vehicle decelerates in order to maintain a constant minimum gap.

So, it can be said that, the subject vehicle always tries to acquire a steady state. Acceleration or deceleration of driver is a dynamic process and occurs in the sequence. A vehicle neither accelerates nor decelerates for an indefinite period of time. The acceleration or deceleration rate is bounded by maximum acceleration rate, maximum deceleration rate and maximum speed of the corresponding vehicle. It means the vehicle driver cannot accelerate beyond the maximum accelerate rate of the vehicle. The vehicle cannot decelerate below the maximum deceleration rate as well. Moreover, the acceleration rate cannot produce speed beyond the maximum speed of the vehicle itself.

There are some other variables which may have a direct or indirect impact on the acceleration (or deceleration) maneuver of the vehicle. Accident or other type of incidents in front of the subject vehicle will likely cause the deceleration of the subject vehicle. The acceleration rate of vehicle in rainfall or snowfall condition is also different from acceleration rate in sunny weather condition.

5.3.3 Acceleration vs. Deceleration

It is fact that, the way of performing acceleration and deceleration is not same for all drivers and not same for a particular driver in different situation and may even differ for a particular driver in identical condition. In this section a number of statistical data will be extracted by analyzing the acceleration and deceleration data. A comparison of the derived data will be shown as well.

Table 5.5 shows some statistics regarding acceleration and deceleration data.

Table 5.5: Statistics from acceleration and deceleration data

Statistical terms	Absolute Value (for acceleration data)	Absolute Value (for deceleration data)
Maximum[1]	5	6
Minimum[2]	0	0.00122
Mean	1.161	0.9195
Standard deviation	1.139	1.039
Mean speed (subject vehicle)	3.511	3.458

[1] The maximum value of acceleration and deceleration has been truncated due to presence of some irregular values

[2] The minimum value of acceleration and deceleration has been truncated due to presence of some irregular values

The values of acceleration and deceleration are in meter per square second. The unit of speed is in meter per second. It is seen that the standard deviation of acceleration and deceleration data is close and the mean speed of the subject vehicle during the acceleration and deceleration maneuvers is very close.

The potential difference between acceleration and deceleration behavior of a random driver is explored in figure C.1 to figure C.6 (Appendix C). It must be noted that the curves are given as an example of a particular vehicle pair only (subject and front direct vehicle involved). The plots from the whole dataset will be a complex one as the behavioral response for acceleration (or deceleration) is not same for every driver and effect of situational constraints.

The units used in the figures C.1 to C.6 are,

- Acceleration or deceleration of the subject vehicle is in meter per square second,
- Subject vehicle speed is in meter per second,
- Front relative spacing is in meter and
- Front relative speed is in meter per second.

The vehicle pair considered to draw the above curves consists of merely a random subject vehicle and its front vehicle (front left in this case). This is a relatively very simple case but has indications about the following:

- The relationship between candidate variables and acceleration is complex and non-linear
- Observed acceleration/deceleration is the result of a combination of variables and the effect of a single variable on acceleration cannot be isolated
- There are significant differences in acceleration and deceleration patterns

Moreover it should be noted that in weak lane situations, the acceleration of the subject vehicle is also likely to be affected by the stimulus from the front direct and front right vehicles in addition to the stimulus from the front left vehicles.

5.3.4 Functional Form

In this research the main focus is to develop an acceleration model for traffic streams having weak lane discipline. In order to get the most suitable model a number of models have been run for acceleration and deceleration data which are presented separately in table 5.10 and table 5.11. The effect of the independent variables used in these models has been discussed already. Some comments are also provided to clarify the performance of model results.

Before presenting the models, the symbols used in the models have been elaborated. The position of subject and front vehicles has been shown in figure 5.13 (actually the figure is redrawn) to facilitate the understanding of the terms.

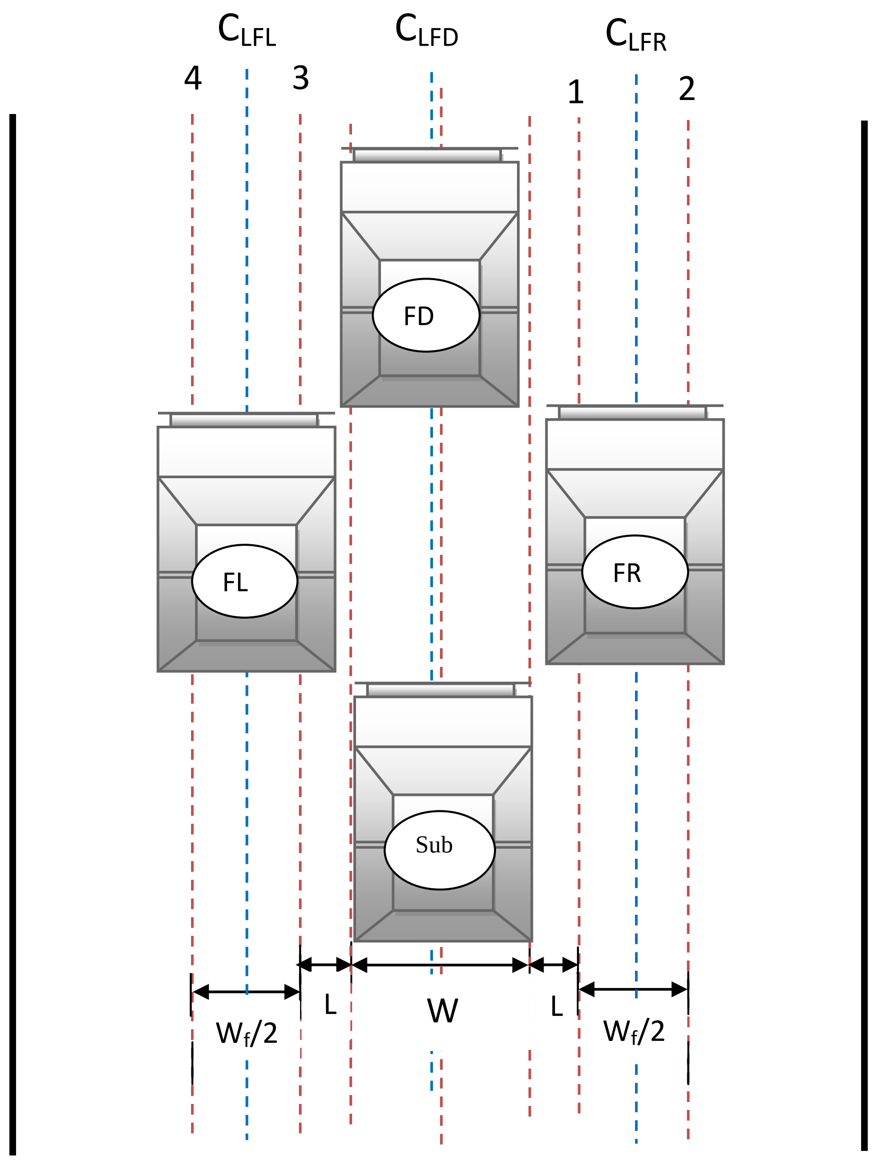


Figure 5.2: Position of subject vehicle and front vehicles

The symbols used for the acceleration and deceleration models are given as follows,

a = acceleration of the subject vehicle

V_{sub} = speed of the subject vehicle

$\Delta V_{front\text{-}left}$ = front left relative speed = speed difference between the front left and subject vehicle

$\Delta X_{front\text{-}left}$ = front left relative spacing = longitudinal clear gap between front left and subject vehicle

$\Delta V_{front\text{-}direct}$ = front direct relative speed = speed difference between the front direct and subject vehicle

$\Delta X_{front\text{-}direct}$ = front direct relative spacing = longitudinal clear gap between front direct and subject vehicle

$\Delta V_{front\text{-}right}$ = front right relative speed = speed difference between the front right and subject vehicle

$\Delta X_{front\text{-}right}$ = front right relative spacing = longitudinal clear gap between front right and subject vehicle

α1, β1, γ1, α2, β2, γ2 ,α3, β3, and γ3 are model parameters associated with their respective variables.

Table 5.6 is shown in the following page followed by table 5.7.

Table 5.6: Functional forms of the acceleration models

Functional form	Adjusted R-squared	Comments
Modified GM Model $a = \{\alpha 1 * (V_{sub}^{\beta 1} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left}^{\gamma 1})\} + \{\alpha 2 * (V_{sub}^{\beta 2} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct}^{\gamma 2})\} + \{\alpha 3 * (V_{sub}^{\beta 3} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right}^{\gamma 3})\}$	-	The model was not estimable due to problem in identifying derivatives from data
Model 1 (modified GM Model without 'γs') $a = \{0.00256 * (V_{sub}^{-0.215} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{0.00818 * (V_{sub}^{0.244} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{0.0252 * (V_{sub}^{-1.57} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0040	
Model 2 (model 1 without 'βs' and 'subject vehicle speed' parameter) $a = \{0.00190 * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{0.0117 * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{0.00277 * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0027	
Model 3 (model 1 without 'βs', 'subject vehicle speed' and 'relative spacing' parameters) $a = (0.292 * \Delta V_{front\text{-}left}) + (0.313 * \Delta V_{front\text{-}direct}) + (0.324 * \Delta V_{front\text{-}right})$	Value= 0.278	Greatest adjusted R-squared value
Model 4 (model 1 without 'βs') $a = \{0.000443 * (V_{sub} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{0.00266 * (V_{sub} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{0.000595 * (V_{sub} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0025	

Model 5 (model 1 without 'β1) a = {0.000443 * (V_{sub} * $\Delta V_{front-left}$)/($\Delta X_{front-left}$)}+ {0.00818 * ($V_{sub}^{0.244}$ * $\Delta V_{front-direct}$)/($\Delta X_{front-direct}$)}+ {0.0252 * ($V_{sub}^{-1.57}$ * $\Delta V_{front-right}$)/($\Delta X_{front-right}$)}	Value= 0.0043	
Model 6 (model 1 without 'front right vehicle' related parameters) a = {0.00257 * ($V_{sub}^{-0.216}$ * $\Delta V_{front-left}$)/($\Delta X_{front-left}$)}+ {0.00818 * ($V_{sub}^{0.245}$ * $\Delta V_{front-direct}$)/($\Delta X_{front-direct}$)}	Value= 0.0010	
Model 7 (model 1 without 'front left vehicle' related parameters) a = {0.00819 * ($V_{sub}^{0.244}$ * $\Delta V_{front-direct}$)/($\Delta X_{front-direct}$)}+ {0.0252 * ($V_{sub}^{-1.57}$ * $\Delta V_{front-right}$)/($\Delta X_{front-right}$)}	Value= 0.0043	
Model 8 (model 1 without 'front direct vehicle' related parameters) a = {0.00256 * ($V_{sub}^{-0.215}$ * $\Delta V_{front-left}$)/($\Delta X_{front-left}$)}+ {0.0252 * ($V_{sub}^{-1.57}$ * $\Delta V_{front-right}$)/($\Delta X_{front-right}$)}	Value= 0.0028	
Model 9 (model 1 without 'β2') a = {0.00256 * ($V_{sub}^{-0.215}$ * $\Delta V_{front-left}$)/($\Delta X_{front-left}$)}+ {0.00266 * (V_{sub} * $\Delta V_{front-direct}$)/($\Delta X_{front-direct}$)}+ {0.0252 * ($V_{sub}^{-1.57}$ * $\Delta V_{front-right}$)/($\Delta X_{front-right}$)}	Value= 0.0043	
Model 10 (model 1 without 'β3) a = {0.00256 * ($V_{sub}^{-0.215}$ * $\Delta V_{front-left}$)/($\Delta X_{front-left}$)}+ {0.00818 * ($V_{sub}^{0.245}$ * $\Delta V_{front-direct}$)/($\Delta X_{front-direct}$)}+ {0.000595 * (V_{sub} * $\Delta V_{front-right}$)/($\Delta X_{front-right}$)}	Value= 0.0018	

Table 5.7: Functional forms of the deceleration models

Functional form	Adjusted R-squared	Comments
Modified GM Model $a = \{\alpha 1 * (V_{sub}^{\beta 1} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left}^{\gamma 1})\} + \{\alpha 2 * (V_{sub}^{\beta 2} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct}^{\gamma 2})\} + \{\alpha 3 * (V_{sub}^{\beta 3} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right}^{\gamma 3})\}$	-	The model was not estimable due to problem in identifying derivatives from data
Model 1 (modified GM Model without 'γs') $a = \{(-0.00127) * (V_{sub}^{-0.137} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{0 * (V_{sub}^{12.0} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{(-0.00000624) * (V_{sub}^{5.42} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0136	
Model 2 (model 1 without 'βs' and 'subject vehicle speed' parameter) $a = \{(-0.00105) * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{(-0.00301) * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{(-0.00704) * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0055	
Model 3 (model 1 without 'βs', 'subject vehicle speed' and 'relative spacing' parameters) $a = ((-0.214) * \Delta V_{front\text{-}left}) + ((-0.209) * \Delta V_{front\text{-}direct}) + ((-0.229) * \Delta V_{front\text{-}right})$	Value= 0.223	Greatest adjusted R-squared value
Model 4 (model 1 without 'βs') $a = \{(-0.000240) * (V_{sub} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{(-0.000856) * (V_{sub} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{(-0.00217) * (V_{sub} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0065	

Model 5 (model 1 without ‘β1) $a = \{(-0.000240) * (V_{sub} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{0 * (V_{sub}^{12.0} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{(-0.00000624) * (V_{sub}^{5.42} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0139	
Model 6 (model 1 without ‘front right vehicle’ related parameters) $a = \{(-0.00128) * (V_{sub}^{-0.1403} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{0 * (V_{sub}^{12.0} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\}$	Value= 0.0055	
Model 7 (model 1 without ‘front left vehicle’ related parameters) $a = \{0 * (V_{sub}^{12.0} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{(-0.00000626) * (V_{sub}^{5.42} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0133	
Model 8 (model 1 without ‘front direct vehicle’ related parameters) $a = \{(-0.00127) * (V_{sub}^{-0.137} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{(-0.00000623) * (V_{sub}^{5.42} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0085	
Model 9 (model 1 without ‘β2’) $a = \{(-0.00127) * (V_{sub}^{-0.137} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{(-0.000855) * (V_{sub} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{(-0.00000623) * (V_{sub}^{5.42} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0094	
Model 10 (model 1 without ‘β3’) $a = \{(-0.00123) * (V_{sub}^{-0.135} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{0 * (V_{sub}^{12.0} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{(-0.00216) * (V_{sub} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$	Value= 0.0104	

The details on the model result is shown in Appendix D (from table D.1 to table D.20).

5.3.5 Selection of Final Acceleration Model

From an analysis of the trial models, it is found that, ‘model 3’ has the best adjusted R-squared value. In terms of the adjusted R-squared values the closest models are ‘model 5’, ‘model 7’ and ‘model 9’ (all have equal Adjusted R-squared value).

‘Model 3’ has the best t-stats as well. Three out of three parameters have significant t-stat value in this model. The closest models are ‘model 2’ (two out of three parameters are significant), and ‘model 9’ (three out of five paramers are significant). Other models do not perform so well in terms of t-stat.

An assumption has been made to select the minimum coefficient value for consideration. In this thesis this value has been taken as 0.1. Using this consideration, ‘model 3’ performs best as three parameters (out of three) have significant coefficient values. In ‘model 1’ three parameters out of six have significant co-efficient values. While in ‘model 6’, ‘model 7’ and ‘model 8’ two parameters out of four have significant coefficient values. In ‘model 9’ two parameters out of five have significant coefficient value.

So, it is found that ‘model 3’ performs better compared to other models based on adjusted R-squared, coefficient and t-stat values. The only drawback of this model is the number of parameters. Only three coefficient values have been estimated from this model and the original model equation involves only these three parameters. This model is linear in nature but the driving behavior is rather complex in nature and the relationship between acceleration and other variables is likely to be non-linear. Moreover, it is suspected that this model overfits the data and may not be flexible enough to perform well in other scenarios (e.g. other sites, other congestion level, etc.).

The model which come close to ‘model 3’ is ‘model 9’. The bright side of ‘model 9’ is that it involves more estimable parameters (five parameters; two more than ‘model 3’). Moreover, in the original equation of ‘model 9’ there are nine parameters (six more than ‘model 3’). ‘Model 9’ is also non-linear in nature which is analogous to the concept of complex driving behavior. So, considering the number of parameters involved and complexity of the driving behavior **‘model 9’** has been selected as the ultimate model for acceleration maneuver of drivers.

The details of final acceleration model is given in table 5.8.

Table 5.8: Details of developed acceleration model

Acceleration Model No. of Observation= 2894 Adjusted R-squared= 0.0043		
Parameter	Value	t-stat
Constant_front left	0.00256	0.12
Constant_front direct	0.00266	2.36
Constant_front right	0.0252	2.68
Beta_subject speed_front left	-0.215	-0.04
Beta_subject speed_front right	-1.57	-13.8

So, the selected acceleration model form is like below,

$a = \{0.00256 * (V_{sub}^{-0.215} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{0.00266 * (V_{sub} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{0.0252 * (V_{sub}^{-1.57} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$

The unit of V_{sub}, $V_{front\text{-}left}$,$V_{front\text{-}direct}$ and $V_{front\text{-}right}$ (speed of subject, front-left, front-direct and front-right vehicle) is in meter per second. The unit of $\Delta V_{front\text{-}left}$, $\Delta V_{front\text{-}direct}$, and $\Delta V_{front\text{-}right}$ (relative speed between front-left and subject, front-direct and subject and front-right and subject vehicle respectively) is in meter per second as well. The unit of $\Delta V_{front\text{-}left}$, $\Delta X_{front\text{-}direct}$, and $\Delta X_{front\text{-}right}$ (relative spacing between front-left and subject, front-direct and subject and front-right and subject vehicle respectively).

5.3.6 Selection of Final Deceleration Model

From an analysis of the trial models, it is found that, 'model 3' has the best adjusted R-squared value. In terms of the adjusted R-squared values the closest models are 'model 5','model 1', 'model 7', 'model 10' and 'model 9'.

'Model 3' has the best t-stat values as well. Three out of three parameters have significant t-stat value in this model. The closest model is 'model 4' in which two parameters (out of three) have significant t-stat value. The nearest model to 'model 4' is 'model 7'(two out of four parameters have significant t-stat values). 'Model 5', 'model 9' and 'model 10' are next. In these models two out of five parameters have significant t-stat values.

An assumption has been made to select the minimum coefficient value for consideration. In this thesis this value has been taken as 0.1. Using this consideration, 'model 3' performs best as three parameters (out of three) have significant coefficient values. In 'model 1' three parameters out of six have significant co-efficient values. While in 'model 6', 'model 7' and 'model 8' two parameters out of four have significant t-stat values. Other models do not perform well in terms of the value of coefficients.

So, it is found that 'model 3' performs better compared to other models based on adjusted R-squared, coefficient and t-stat values. The only drawback of this model is the number of parameters. Only three coefficient values have been estimated from this model and the original model equation involves only these three parameters. This model is linear in nature but the driving behavior is rather complex in nature and the relationship between acceleration and other variables is likely to be non-linear. Moreover, it is suspected that this model overfits the data and may not be flexible enough to perform well in other scenarios (e.g. other sites, other congestion level, etc.).

Apart from 'model 3', it has been found that 'model 7' and 'model 9' performs so close that it is not easy to select from these two. There is a trade off here. 'Model 7' has slightly better adjusted R-squared and t-stat value. But in terms of co-efficient value, 'model 9' performs better. Taking this into consideration 'model 9' has been selected over 'model 7'.

The final choice will be between 'model 3' and 'model 9'. The bright side of 'model 9' is that this model considers more parameters in estimation (five parameters; two more than 'model 3'). Moreover, in the original model equation, there are nine parameters (six more than 'model 3'). This model is non-linear as well which is more likely to represent the complex driving scenario. So taking into consideration the number of parameters and non-linearity of the model (analogous to complex driving behavior), it can be deduced that **'model 9'** will be the ultimate model for deceleration scenario.

The details of final deceleration model is given in figure 5.9.

Table 5.9: Details of developed deceleration model

Deceleration Model No. of Observation= 3024 Adjusted R-squared= 0.0094		
Parameter	Value	t-stat
Constant_front left	-0.00127	-0.17
Constant_front direct	-0.000855	-1.98
Constant_front right	-0.00000623	-0.66
Beta_subject speed_front left	-0.137	-0.03
Beta_subject speed_front right	5.42	5.41

The deceleration model form will be as follows,

$a = \{(-0.00127) * (V_{sub}^{-0.137} * \Delta V_{front\text{-}left})/(\Delta X_{front\text{-}left})\} + \{(-0.000855) * (V_{sub} * \Delta V_{front\text{-}direct})/(\Delta X_{front\text{-}direct})\} + \{(-0.00000623) * (V_{sub}^{5.42} * \Delta V_{front\text{-}right})/(\Delta X_{front\text{-}right})\}$

The unit of V_{sub}, $V_{front\text{-}left}$,$V_{front\text{-}direct}$ and $V_{front\text{-}right}$ (speed of subject, front-left, front-direct and front-right vehicle) is in meter per second. The unit of $\Delta V_{front\text{-}left}$, $\Delta V_{front\text{-}direct}$, and $\Delta V_{front\text{-}right}$ (relative speed between front-left and subject, front-direct and subject and front-right and subject vehicle respectively) is in meter per second as well. The unit of $\Delta V_{front\text{-}left}$, $\Delta X_{front\text{-}direct}$, and $\Delta X_{front\text{-}right}$ (relative spacing between front-left and subject, front-direct and subject and front-right and subject vehicle respectively).

5.4 Summary

In this chapter data processing has been performed to gain trajectory of vehicles and obtain vehicle composition in the traffic stream. Later ‘MATLAB’ code has been utilized to generate variables for acceleration and deceleration models. The effect of reaction time has been shown prior to the final analysis and model formulation to make the models more logical in nature. At the end of the analysis separate acceleration and deceleration model equations have been developed to show the effect of different factors (independent variables) on acceleration and deceleration maneuvers.

Chapter 6

Conclusions

6.1 Summary of Research

The present study aimed to develop acceleration model for traffic stream maintaining weak lane discipline. In the earlier chapters of the thesis the methodology for formulation of the model has been discussed. Data collection plan has also been finalized in the initial level. Type one or disaggregate data consists of video data and GPS data. Video data have later been processed by Image Processing Software TRAZER in order to give vehicle counts, flow, occupancy and trajectory. Trajectories of vehicles have been analyzed to generate variables required for development of acceleration models. Effect of reaction time has been analyzed for final selection of reaction time to develop the acceleration models. Preliminary analysis revealed substantial differences in acceleration and deceleration maneuvers. Therefore, the dataset was divided into acceleration data and deceleration data and two separate models were developed. A number of models have been run in software 'STATA SE 11' in order to obtain the best model which best fit the acceleration and deceleration data. It may be noted that in contrary to previous models for heterogeneous traffic (which only consider a single front vehicle as the leader), the model proposed in this thesis explicitly takes into effect the influences of all three front vehicles (front left, front direct and front right). Therefore, the parameters used in the finally selected acceleration model are acceleration of the subject vehicle, speed of the subject vehicle, the relative speed between front vehicles and subject vehicle and spacing between front vehicles and subject vehicle. The number of variables for acceleration and deceleration models is same, but the number of parameters in deceleration model is greater than that of acceleration model. At the end of the analysis the results of the test models have been presented. The details of the selected acceleration models have been provided as well.

6.2 Main Features of the Model

It has been already mentioned that acceleration and deceleration data has been analyzed separately after selection of reaction time. So, two models have been developed; one for acceleration decision and another for deceleration decision. The main features of the models include the following,

- The models can take all the front vehicles (e.g. front left, front direct and front right) at the same time and show their combined effect on the acceleration (or, deceleration) operation of the subject vehicle driver
- The models are based on a fairly good number of observations extracted from detailed vehicle trajectories and therefore the reliability is reasonable
- The models can predict the possible action of the subject vehicle driver if inputs (variables) are provided properly
- The models have flexibility to alter the number of parameters and can be quickly recalibrated to a new scenario if required

The end product of this thesis is a set of models that can predict acceleration decisions of drivers in weak lane discipline in different neighboring conditions. The key findings of the research are given as following:

(1) Acceleration decisions of drivers in weak lane situations are affected by front left and front right vehicles in addition to front direct vehicle.
(2) The key function of both the acceleration and deceleration models is non-linear.
(3) The key variables that affect acceleration and deceleration behavior are same, but the functional forms of the models are different.

6.3 Recommendations for Further Work

In this subsection the limitations of the research have been identified and based on the drawbacks some recommendations have been made to complement the models and the overall research. The recommendation for further work are presented below,

1. The effect of demographic factors (e.g. age, gender, driving experience, alcohol addiction) could not been addressed. The inclusion of these factors can make the models more reasonable.

2. The effect of the type of front vehicles and subject vehicle can be analyzed used to make more advanced acceleration models.

3. Reaction time can be tested across a number of models to get a better output and make the models more logical.

4. This thesis could not show the effect of density variation as the data was collected for a particular period of time. If data can be collected for different time duration, then the effect of density can be understood.

5. More complex functional form of the models can be tested.

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Appendices

Appendix A

<u>Reaction time estimation resulting from secondary data</u>

Table A.1: Estimation result using reaction time of 0 second

Full Data		
No. of observation = 206 Adjusted R-square = 0.3145		
Parameter	Value	T-stat
Alpha	0.8863962	2.91
Beta_speed	-0.0269324	-0.21
Beta_relative spacing	0.3998009	1.56
Acceleration Data		
No. of observation = 129 Adjusted R-square = 0.3077		
Parameter	Value	T-stat
Alpha	0.9488253	2.26
Beta_speed	-0.0568405	-0.41
Beta_relative spacing	0.5311533	1.59
Deceleration Data		
No. of observation = 77 Adjusted R-square = 0.3245		
Parameter	Value	T-stat
Alpha	0.9835289	1.64
Beta_speed	0.0188392	0.04
Beta_relative spacing	0.3465262	0.56

Table A.2: Estimation result using reaction time of 0.25 second

Full Data		
No. of observation = 206 Adjusted R-square = 0.3841		
Parameter	Value	T-stat
Alpha	1.087069	3.50
Beta_speed	-0.0884786	-0.75
Beta_relative spacing	0.488625	2.07
Acceleration Data		
No. of observation = 129 Adjusted R-square = 0.3719		
Parameter	Value	T-stat
Alpha	0.9093427	2.80
Beta_speed	-0.0653636	-0.47
Beta_relative spacing	0.4822397	1.65
Deceleration Data		
No. of observation = 77 Adjusted R-square = 0.4377		
Parameter	Value	T-stat
Alpha	2.208643	2.08
Beta_speed	-0.34255	-0.98
Beta_relative spacing	0.5844953	1.10

Table A.3: Estimation result using reaction time of 0.5 second

Full Data		
No. of observation = 199 Adjusted R-square = 0.4059		
Parameter	Value	T-stat
Alpha	1.247833	3.40
Beta_speed	-0.2079166	-1.72
Beta_relative spacing	0.5226016	2.10
Acceleration Data		
No. of observation = 124 Adjusted R-square = 0.4049		
Parameter	Value	T-stat
Alpha	1.123662	2.64
Beta_speed	-0.1734319	-1.22
Beta_relative spacing	0.5463599	1.73
Deceleration Data		
No. of observation = 75 Adjusted R-square = 0.4131		
Parameter	Value	T-stat
Alpha	2.084549	1.84
Beta_speed	-0.1911616	-0.59
Beta_relative spacing	0.756896	1.37

Table A.4: Estimation result using reaction time of 0.75 second

Full Data		
No. of observation = 195 Adjusted R-square = 0.3783		
Parameter	Value	T-stat
Alpha	1.199559	3.13
Beta_speed	-0.2625304	-1.98
Beta_relative spacing	0.4973598	1.82
Acceleration Data		
No. of observation = 115 Adjusted R-square = 0.3898		
Parameter	Value	T-stat
Alpha	1.139309	2.34
Beta_speed	-0.2123359	-1.22
Beta_relative spacing	0.5478125	1.57
Deceleration Data		
No. of observation = 80 Adjusted R-square = 0.3490		
Parameter	Value	T-stat
Alpha	1.917574	1.51
Beta_speed	-0.1505636	-0.51
Beta_relative spacing	0.8246145	1.36

Table A.5: Estimation result using reaction time of 1.0 second

Full Data		
No. of observation = 189 Adjusted R-square = 0.3542		
Parameter	Value	T-stat
Alpha	1.064264	2.86
Beta_speed	-0.2366115	-1.86
Beta_relative spacing	0.4596824	1.56
Acceleration Data		
No. of observation = 111 Adjusted R-square = 0.3975		
Parameter	Value	T-stat
Alpha	1.041528	2.20
Beta_speed	-0.1406384	-0.71
Beta_relative spacing	0.522102	1.51
Deceleration Data		
No. of observation = 78 Adjusted R-square = 0.2840		
Parameter	Value	T-stat
Alpha	0.2269143	0.59
Beta_speed	-0.6979346	-1.28
Beta_relative spacing	-0.8295179	-0.60

Acceleration vs. subject speed

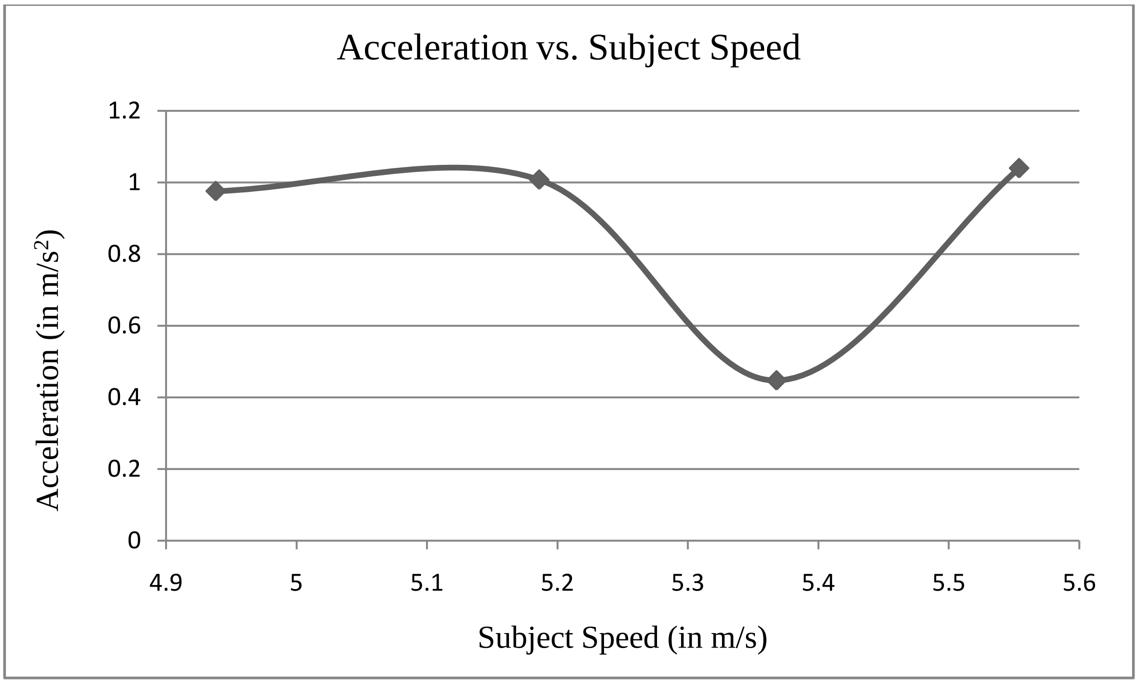

Figure A.1: Acceleration vs. subject speed (secondary data)

Acceleration vs. front relative speed

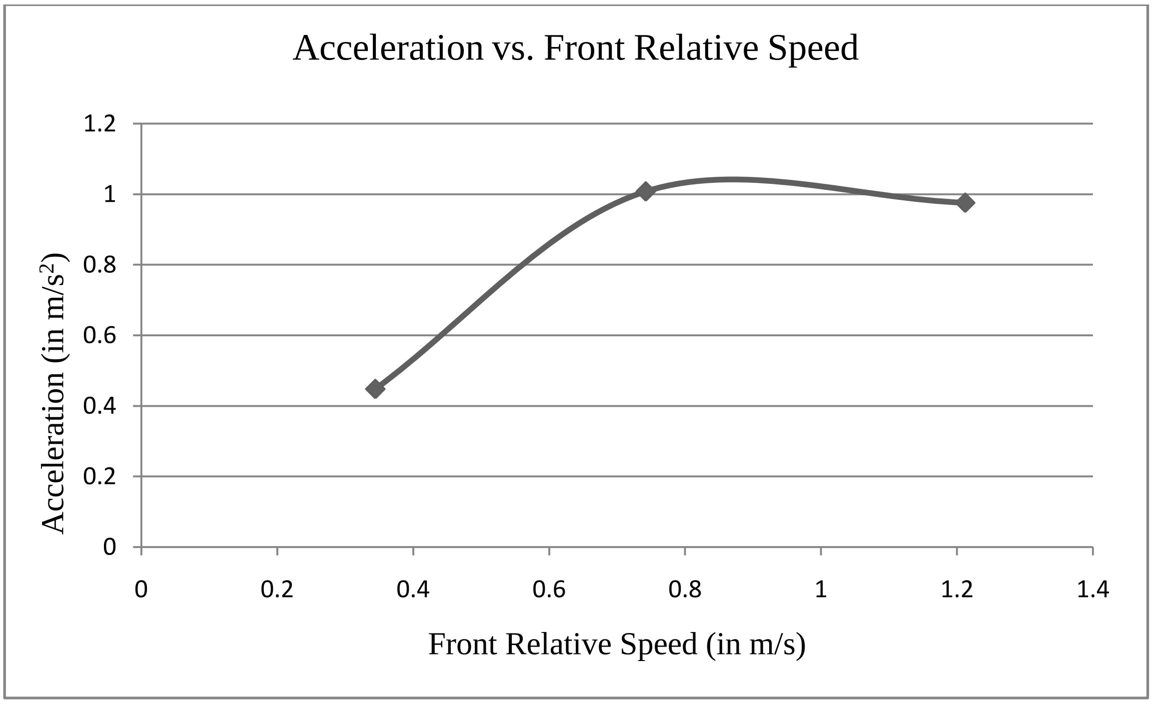

Figure A.2: Acceleration vs. front relative speed (secondary data)

Acceleration vs. front relative spacing

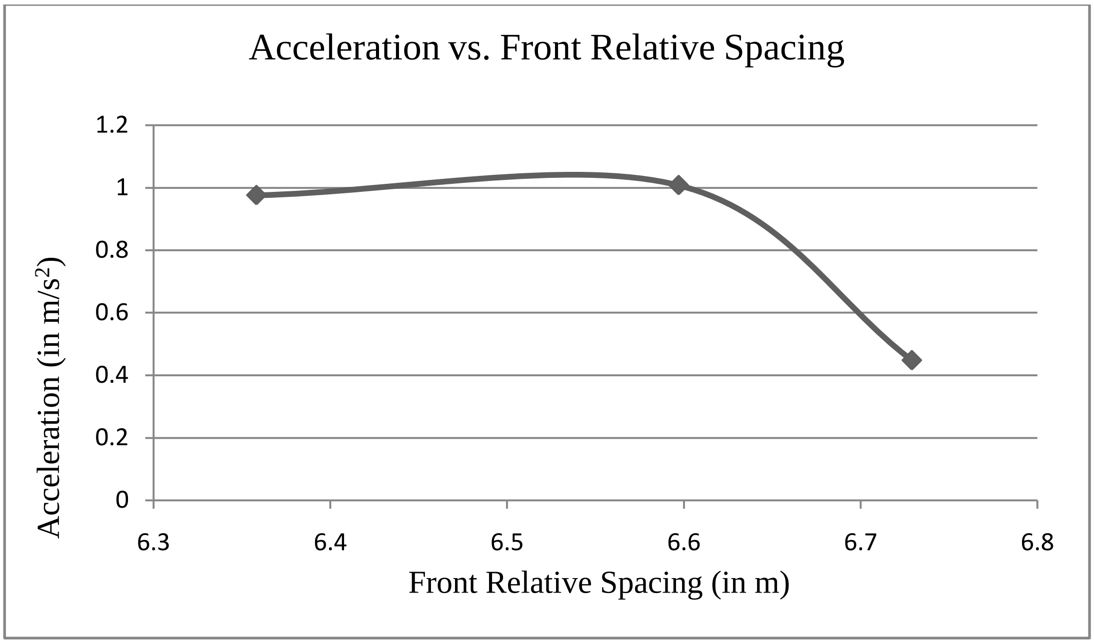

Figure A.3: Acceleration vs. front relative spacing (secondary data)

Deceleration vs. subject speed

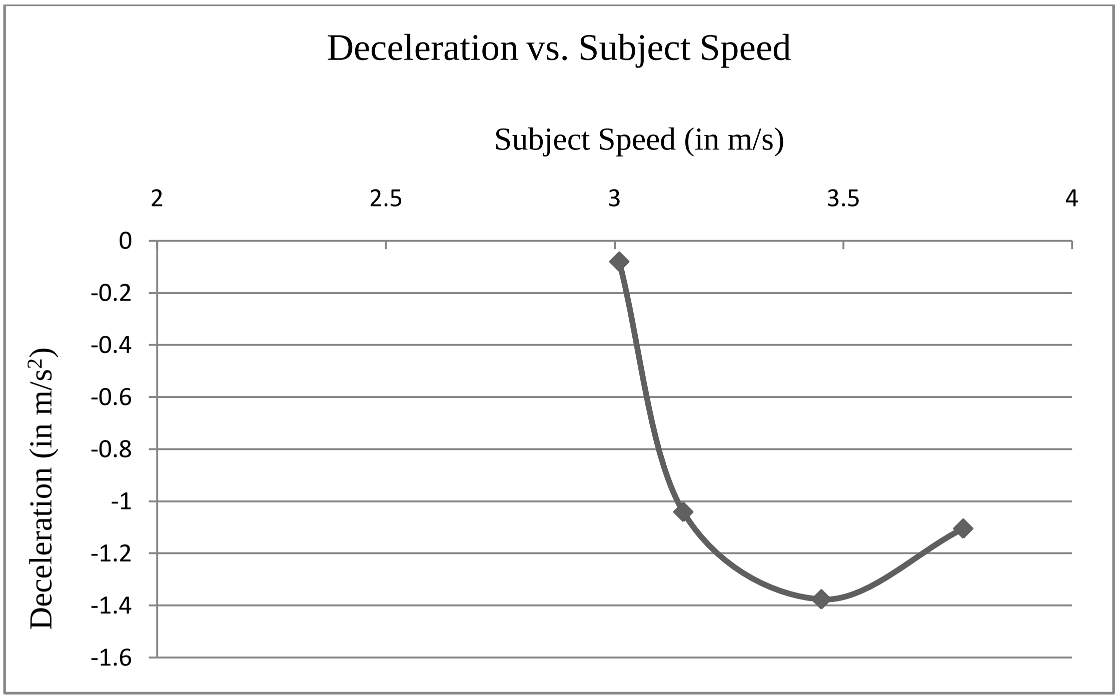

Figure A.4: Deceleration vs. subject speed (secondary data)

Deceleration vs. front relative speed

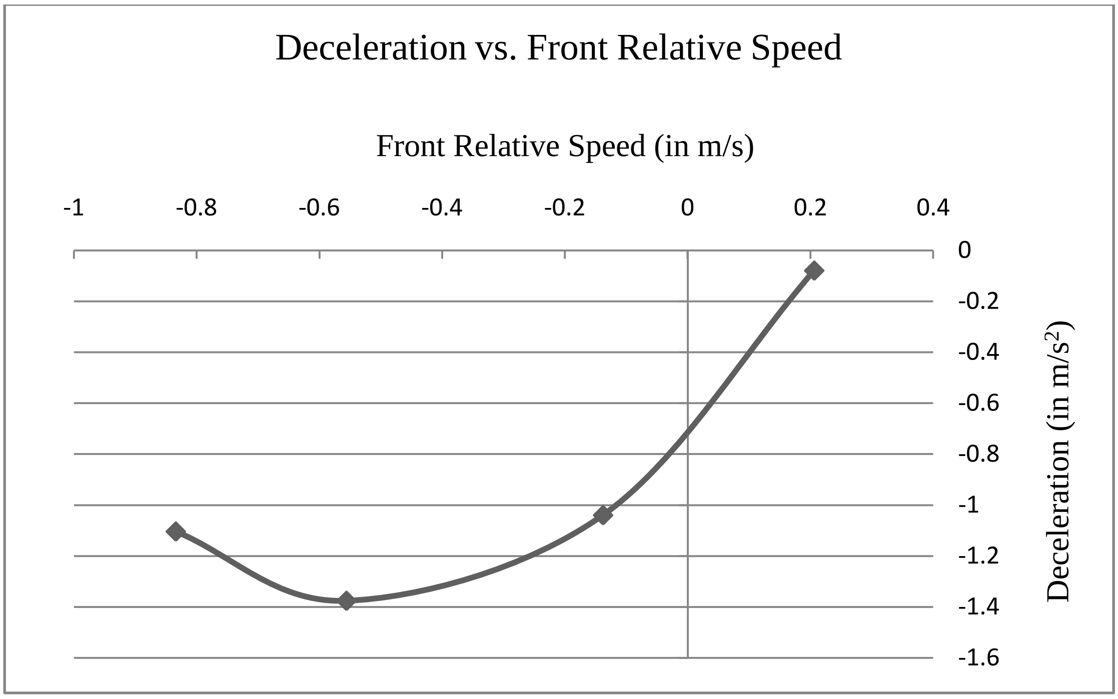

Figure A.5: Deceleration vs. front relative speed (secondary data)

Deceleration vs. front relative spacing

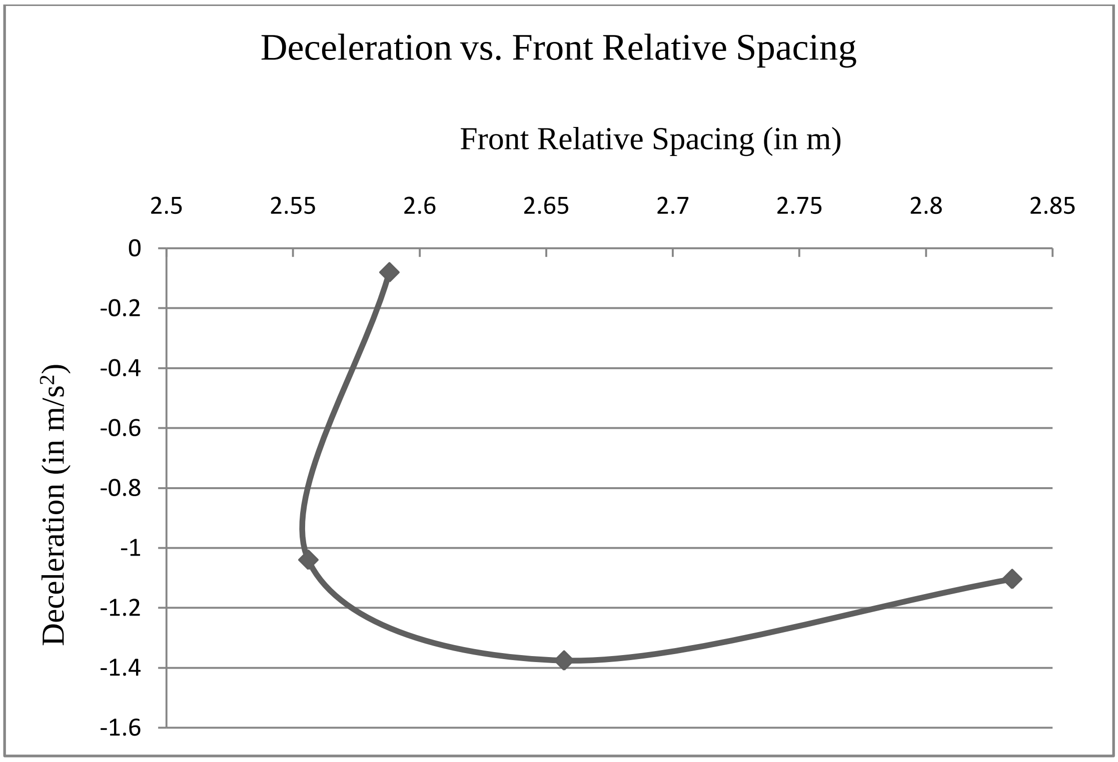

Figure A.6: Deceleration vs. front relative spacing (secondary data)

Appendix B

'MATLAB' Variable Generation Code

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Separates timing and co-ordinate data of each vehicle.                %
% Calculates x & y velocity and acceleration.                           %
% Final Output is a array of cells, containing vehicle wise data in each  %
% element. co-ordinates, velocity & acceleration data all are smoothed.   %
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


clear all;
warning off;


FRAME_PER_SEC = 25;
V_ID_COL = 2;
FRAME_NUM_COL = 1;
X_COL = 3;
Y_COL = 4;
POLY_ORDER = 5;
INTERVAL = 0.1;
TH_THRES = 3;
LAT_SAFETY_MARGIN = 0.25;


hv_lookup = [0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0];
h_lookup = [4.54, 4.47, 4.29, 5.78, 5.5, 2.63, 8.46, 6.7, 2.13, 1.78, 2.51];
w_lookup = [1.76, 2.13, 1.78, 2.02, 1.8, 1.3, 2.46, 2.44, .75, .61, 1.22];
```

```
data = csvread('trajectory_m.csv',1,0);
data_id = csvread('Vehicle_ID.csv');

[vua,index] = sort(data(:, V_ID_COL));
sort_data = data(index, :);

v_id = [];
v_data = {};
i = 1;
init = 1;
LAST_ID = sort_data(end, V_ID_COL);

while 1
   v_id(i) = sort_data(init, V_ID_COL);
   last = find(sort_data(:, V_ID_COL) == v_id(i), 1, 'last');

   if(ismember(v_id(i), data_id(:,2)) == 0)
      if(v_id(i) == LAST_ID)
         break;
      end
      init = last + 1;
      continue;
   end

   v_data_new = sort_data(init:last, [FRAME_NUM_COL, X_COL, Y_COL]);
   nn = find(data_id(:,2) == v_id(i));
   for j = 3:(find(isnan(data_id(nn, :)), 1, 'first') - 1)
```

```
        temp_id = data_id(nn, j);
        condition = (sort_data(:, V_ID_COL) == temp_id) & (ismember(sort_data(:,
FRAME_NUM_COL), v_data_new(:,1)) == 0);
        cond_data = sort_data(find(condition), [FRAME_NUM_COL, X_COL,
Y_COL]);
        for k = 1:size(cond_data, 1)
            if (sum(cond_data(k,3) <= v_data_new(:,3)) == size(v_data_new,1))
                v_data_new = [v_data_new; cond_data(k,:)];
            end
        end
    end

    t = v_data_new(:,1) / FRAME_PER_SEC;
    t_div = (double(int32(t(1)/INTERVAL))*INTERVAL : INTERVAL :
double(int32(t(end)/INTERVAL))*INTERVAL)';

    x_loc = polyval(polyfit(t, v_data_new(:,2), POLY_ORDER), t_div);
    y_loc = polyval(polyfit(t, v_data_new(:,3), POLY_ORDER), t_div);

    x_velocity = (x_loc(2:end) - x_loc(1:end-1)) ./ INTERVAL;
    y_velocity = (y_loc(2:end) - y_loc(1:end-1)) ./ INTERVAL;
    x_acceleration = (x_velocity(2:end) - x_velocity(1:end-1)) ./ INTERVAL;
    y_acceleration = (y_velocity(2:end) - y_velocity(1:end-1)) ./ INTERVAL;

    t_div = t_div(3:end);
    x_loc = x_loc(3:end);
    y_loc = y_loc(3:end);
    x_velocity = polyval(polyfit(t_div, x_velocity(2:end), POLY_ORDER), t_div);
```

```
    y_velocity = polyval(polyfit(t_div, y_velocity(2:end), POLY_ORDER), t_div);

    x_acceleration = polyval(polyfit(t_div, x_acceleration, POLY_ORDER), t_div);

    y_acceleration = polyval(polyfit(t_div, y_acceleration, POLY_ORDER), t_div);


    v_data(i) = {[t_div, v_id(i)*ones(length(x_acceleration),1), x_loc, y_loc,
x_velocity, x_acceleration, y_velocity, y_acceleration, data_id(nn,
1)*ones(length(x_acceleration),1), w_lookup(data_id(nn,
1))*ones(length(x_acceleration),1), hv_lookup(data_id(nn,
1))*ones(length(x_acceleration),1)]};


    if(v_id(i) == LAST_ID)

        break;

    end


    i = i + 1;

    init = last + 1;

end


ret = cell2mat(v_data');


% v_ind = [];

% for i = min(ret(:,FRAME_NUM_COL)) : INTERVAL :
max(ret(:,FRAME_NUM_COL))

%     if sum(ret(:,FRAME_NUM_COL) == i) > 1

%         v_ind = [v_ind i];

%     end

% end

%

% ind = ismember(ret(:,FRAME_NUM_COL), v_ind);
```

```
pair_data = ret;%(ind,:);


[vua,index] = sort(pair_data(:, FRAME_NUM_COL));
sort_pair_data = pair_data(index, :);
sort_pair_data(:,12:44) = NaN;


for i = 1:size(sort_pair_data,1)
    sv_t = sort_pair_data(i,1);
    sv_id = sort_pair_data(i,2);
    sv_x = sort_pair_data(i,3);
    sv_y = sort_pair_data(i,4);
    sv_vy = sort_pair_data(i,7);


    W = sort_pair_data(i,10);
    margin = LAT_SAFETY_MARGIN;
    lim_l = sv_x - W/2 - margin;
    lim_r = sv_x + W/2 + margin;
    lim_step = (lim_r - lim_l) / 3;
    lim_ml = lim_l + lim_step;
    lim_mr = lim_r - lim_step;


    ind = (sort_pair_data(:,1) == sv_t) & (sort_pair_data(:,2) ~= sv_id);
    temp_id = sort_pair_data(ind,2);
    temp_x = sort_pair_data(ind,3);
    temp_y = sort_pair_data(ind,4);
    temp_va = sort_pair_data(ind,5:8);
    H = h_lookup(sort_pair_data(ind,9))';
```

```
    hv = sort_pair_data(ind,11);
    temp_type = sort_pair_data(ind,9);
    temp_y = (temp_y + H);
    sp = abs(temp_y - sv_y);
    th = sp/sv_vy;

    t_Wd2 = w_lookup(sort_pair_data(ind,9))' / 2;
    temp_xl = temp_x - t_Wd2;
    temp_xr = temp_x + t_Wd2;

    ind_f = (temp_y < sv_y) & (th <= TH_THRES);

    ind_f_l = (temp_xr > lim_l) & (temp_x < lim_ml) & ind_f;
    l_id = temp_id(ind_f_l);
    l_y = temp_y(ind_f_l);
    [vua,t_ind] = max(l_y);
    if(isempty(t_ind)==0)
        ttt_ind = (temp_id == l_id(t_ind));
        l_data = temp_va(ttt_ind,:);
        sort_pair_data(i,12:17) = [l_id(t_ind), temp_type(ttt_ind), l_data];
        sort_pair_data(i,18:22) = [l_data(3)-sv_vy, sp(ttt_ind), th(ttt_ind), H(ttt_ind),
hv(ttt_ind)];
    end

    ind_f_c = (temp_x >= lim_ml) & (temp_x <= lim_mr) & ind_f;
    c_id = temp_id(ind_f_c);
    c_y = temp_y(ind_f_c);
```

```
    [vua,t_ind] = max(c_y);

    if(isempty(t_ind)==0)

        ttt_ind = (temp_id == c_id(t_ind));

        c_data = temp_va(ttt_ind,:);

        sort_pair_data(i,23:28) = [c_id(t_ind), temp_type(ttt_ind), c_data];

        sort_pair_data(i,29:33) = [c_data(3)-sv_vy, sp(ttt_ind), th(ttt_ind), H(ttt_ind),
hv(ttt_ind)];

    end


    ind_f_r = (temp_x > lim_mr) & (temp_xl < lim_r) & ind_f;

    r_id = temp_id(ind_f_r);

    r_y = temp_y(ind_f_r);

    [vua,t_ind] = max(r_y);

    if(isempty(t_ind)==0)

        ttt_ind = (temp_id == r_id(t_ind));

        r_data = temp_va(ttt_ind,:);

        sort_pair_data(i,34:39) = [r_id(t_ind), temp_type(ttt_ind), r_data];

        sort_pair_data(i,40:44) = [r_data(3)-sv_vy, sp(ttt_ind), th(ttt_ind), H(ttt_ind),
hv(ttt_ind)];

    end


end


% uncomment to remove frames with no front vehicle.

%

% init = 1;

% while 1

%     v_time = sort_pair_data(init,1);
```

```
%    last = find(sort_pair_data(:, 1) == v_time, 1, 'last');

%    test = sort_pair_data(init:last, 12:44);

%    if (sum(sum(isnan(test))) == size(test,1)*size(test,2)) & (size(test,1)*size(test,2)
~= 0)

%        sort_pair_data(init:last, :) = [];

%    else

%        init = last + 1;

%    end

%

%    if(init > size(sort_pair_data,1))

%        break;

%    end

% end


% uncomment to remove rows with no front vehicle

%

remove_index = sum(isnan(sort_pair_data(:, 12:44)),2) == 33;

sort_pair_data(remove_index, :) = [];


title = {'Frame_ID', 'SV_ID', 'SV_X', 'SV_Y', 'SV_Vx', 'SV_Ax', 'SV_Vy', 'SV_Ay',
'SV_Type', 'SV_Width', 'SV_HVD', 'FLV_ID', 'FLV_Type', 'FLV_Vx', 'FLV_Ax',
'FLV_Vy', 'FLV_Ay', 'FLV_RVy', 'FLV_Spacing', 'FLV_TH', 'FLV_Length',
'FLV_HVD', 'FDV_ID', 'FDV_Type', 'FDV_Vx', 'FDV_Ax', 'FDV_Vy', 'FDV_Ay',
'FDV_RVy', 'FDV_Spacing', 'FDV_TH', 'FDV_Length', 'FDV_HVD', 'FRV_ID',
'FRV_Type', 'FRV_Vx', 'FRV_Ax', 'FRV_Vy', 'FRV_Ay', 'FRV_RVy',
'FRV_Spacing', 'FRV_TH', 'FRV_Length', 'FRV_HVD'};


xlswrite('results.xls', title, 1, 'A1:AR1');

xlswrite('results.xls', sort_pair_data, 1, ['A2:AR' num2str(size(sort_pair_data,1)+1)]);
```

<u>‘STATA SE 11’ Commands for Running Acceleration/Deceleration Models</u>

File Loader command

```
insheet using "F:\Education\CE 6000_RUPAM\Data\Primary Data Related\From Asad Gate\Analysis of Data_1hr\Input file\Full data estimation\all front vehicle_full_clean_renamed2.csv"
```

Execution files

Modified GM

```
nl(v1=[{alpha}*v5*v3^{beta}]/[v6^{gamma}]+[{alpha2}*v10*v3^{beta2}]/[v11^{gamma2}]+[{alpha3}*v15*v3^{beta3}]/[v16^{gamma3}])
```

Model 1 (Modified GM Model without 'gammas')

```
nl(v1=[{alpha}*v5*v3^{beta}]/[v6]+[{alpha2}*v10*v3^{beta2}]/[v11]+[{alpha3}*v15*v3^{beta3}]/[v16])
```

Model 2 (Model 1 without 'betas' and 'subject vehicle speed' parameters)

```
nl (v1=[{alpha}*v5]/[v6]+[{alpha2}*v10]/[v11]+[{alpha3}*v15]/[v16])
```

Model 3 (Model 1 without 'betas','subject vehicle speed' and 'relative spacing' parameters)

```
nl (v1=[{alpha}*v5]+[{alpha2}*v10]+[{alpha3}*v15])
```

Model 4 (Model 1 without 'betas')

```
nl (v1=[{alpha}*v5*v3]/[v6]+[{alpha2}*v10*v3]/[v11]+[{alpha3}*v15*v3]/[v16])
```

Model 5 (Model 1 without 'beta')

```
nl(v1=[{alpha}*v5*v3]/[v6]+[{alpha2}*v10*v3^{beta2}]/[v11]+[{alpha3}*v15*v3^{beta3}]/[v16])
```

Model 6 (Model 1 without 'front right vehicle' related parameters)

```
nl (v1=[{alpha}*v5*v3^{beta}]/[v6]+[{alpha2}*v10*v3^{beta2}]/[v11])
```

Model 7 (Model 1 without 'front left vehicle' related parameters)

```
nl (v1=[{alpha2}*v10*v3^{beta2}]/[v11]+[{alpha3}*v15*v3^{beta3}]/[v16])
```

Model 8 (Model 1 without 'front direct vehicle' related parameters)

```
nl (v1=[{alpha}*v5*v3^{beta}]/[v6]+[{alpha3}*v15*v3^{beta3}]/[v16])
```

Model 9 (Model 1 without 'beta2')

nl(v1=[{alpha}*v5*v3^{beta}]/[v6]+[{alpha2}*v10*v3]/[v11]+[{alpha3}*v15*v3^{beta3}]/[v16])

Model 10 (Model 1 without 'beta3')

nl(v1=[{alpha}*v5*v3^{beta}]/[v6]+[{alpha2}*v10*v3^{beta2}]/[v11]+[{alpha3}*v15*v3]/[v16])

Appendix C

Acceleration vs. subject speed curve

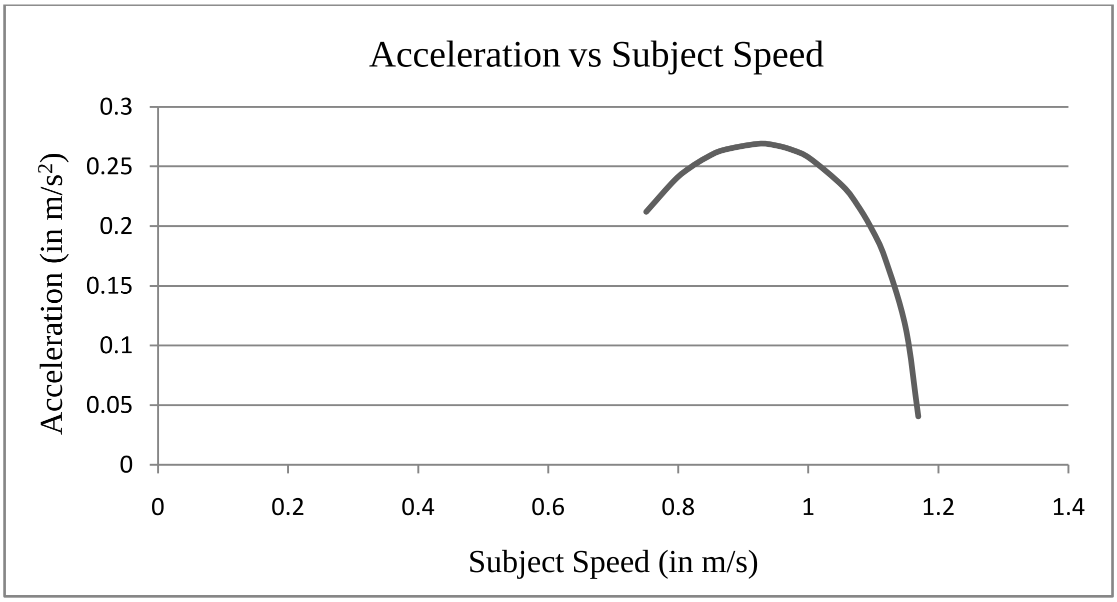

Figure C.1: Acceleration vs. subject speed (primary data)

Acceleration vs. front relative speed curve

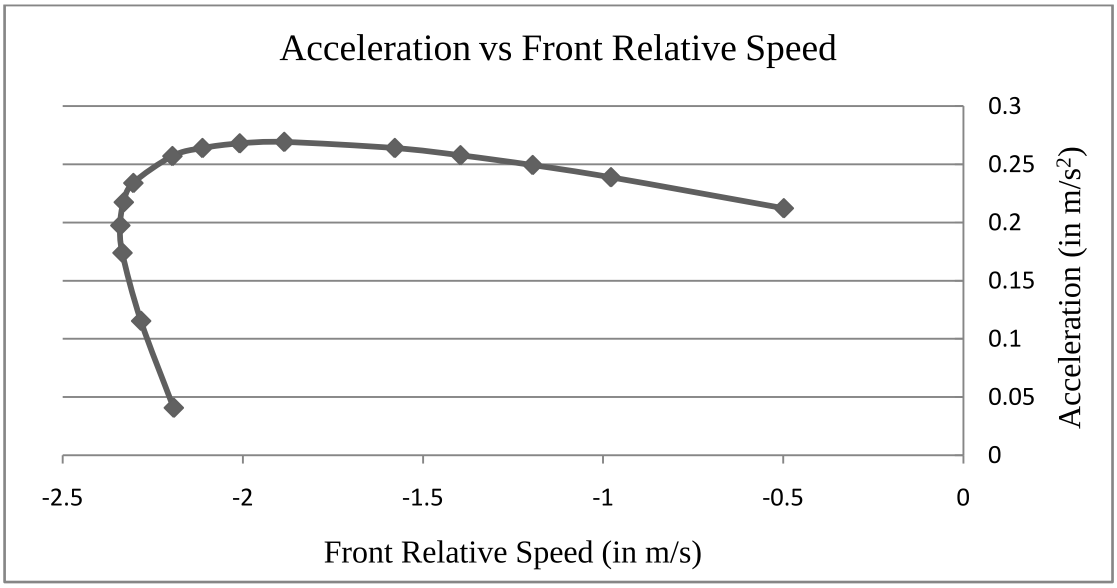

Figure C.2: Acceleration vs. front relative speed (primary data)

Acceleration vs. front relative spacing curve

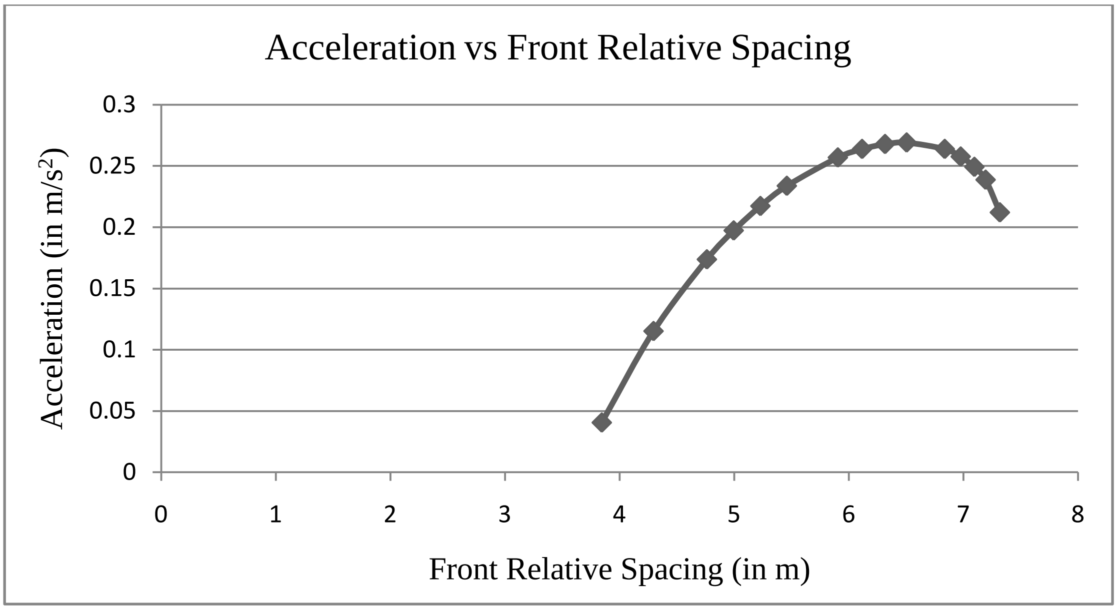

Figure C.3: Acceleration vs. front relative spacing (primary data)

Deceleration vs. subject speed curve

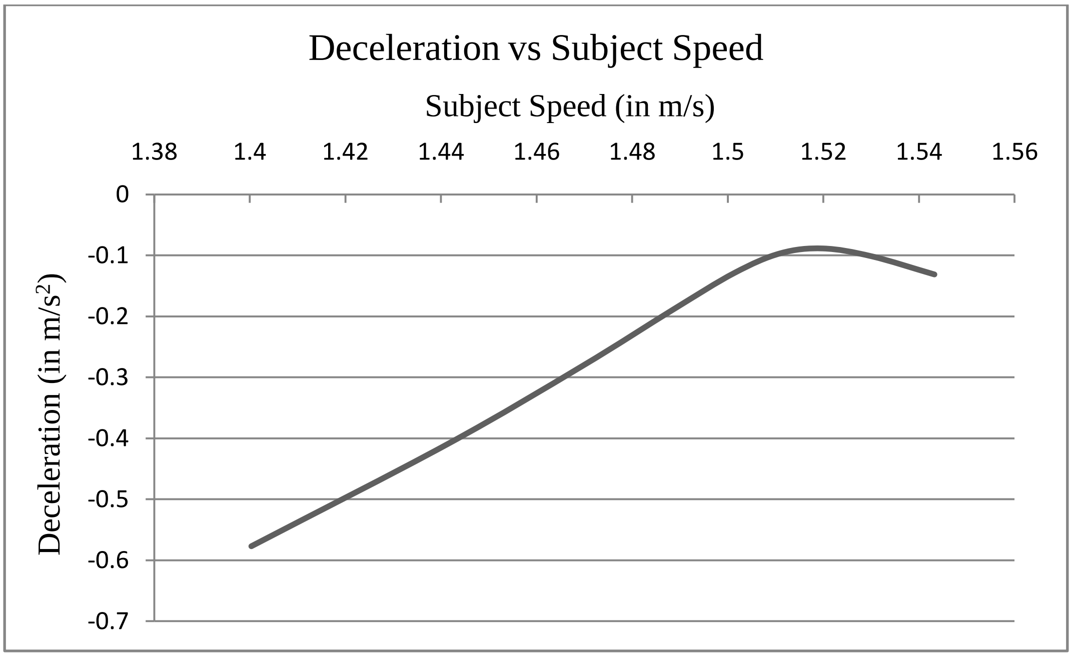

Figure C.4: Deceleration vs. subject speed (primary data)

Deceleration vs. front relative speed curve

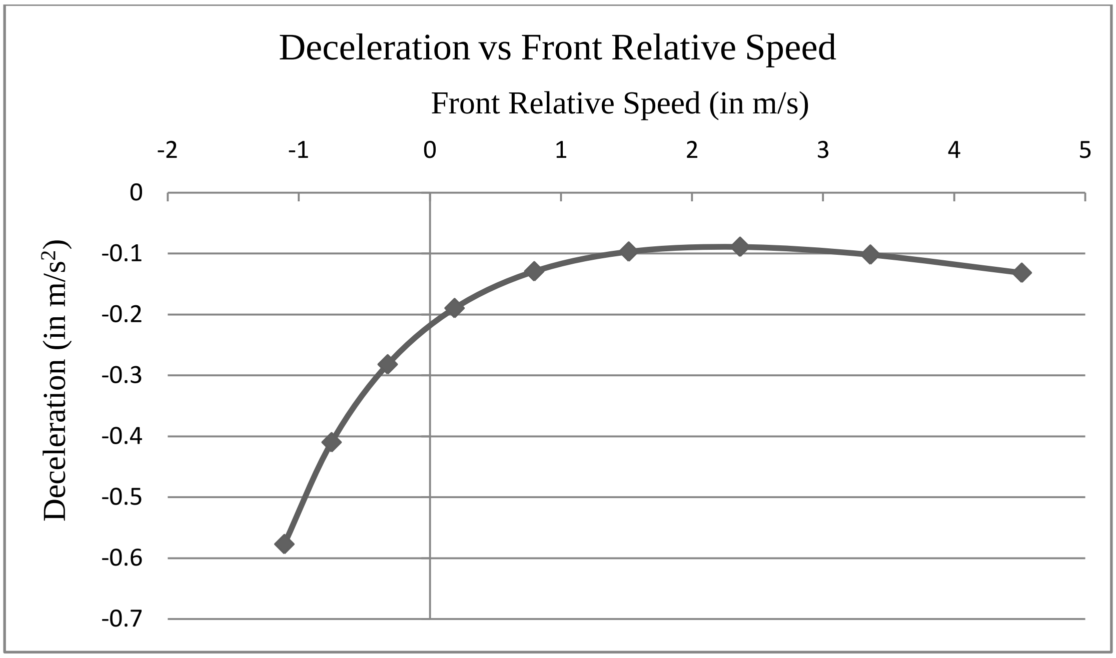

Figure C.5: Deceleration vs. front relative speed (primary data)

Deceleration vs. front relative spacing curve

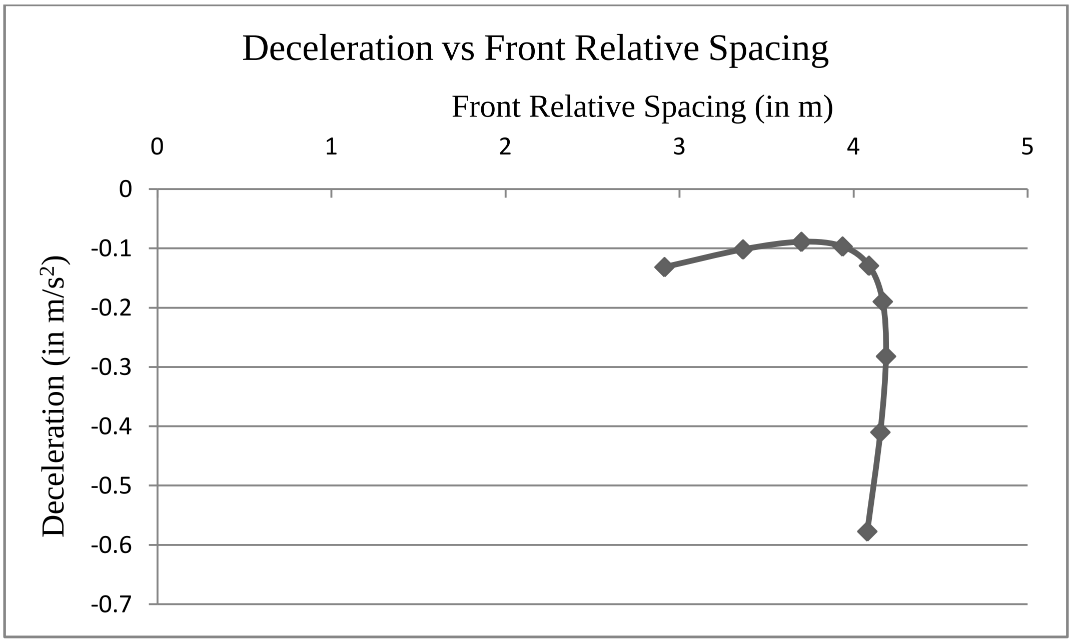

Figure C.6: Deceleration vs. front relative spacing (primary data)

Appendix D

Details of Model Results

Acceleration Models

Table D.1: Estimation result for Model 1 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0040 Root MSE = 1.62			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.00256	0.12	0.020804
beta	-0.215	-0.04	5.89
alpha2	0.00818	0.16	0.0513
beta2	0.244	0.06	4.24
alpha3	0.0252	2.68	0.00942
beta3	-1.57	-13.8	0.114

Table D.2: Estimation result for Model 2 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0027 Root MSE = 1.62			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.00190	1.13	0.00169
alpha2	0.0117	2.36	0.00496
alpha3	0.00277	1.99	0.00139

Table D.3: Estimation result for Model 3 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.278 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.292	20.80	0.01405
alpha2	0.313	14.00	0.0224
alpha3	0.324	19.8	0.0164

Table D.4: Estimation result for Model 4 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0025 Root MSE = 1.62			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.000443	1.06	0.000417
alpha2	0.00266	2.36	0.00113
alpha3	0.000595	1.87	0.000319

Table D.5: Estimation result for Model 5 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0043 Root MSE = 1.62			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.000443	1.06	0.000417
alpha2	0.00818	0.160	0.0513
beta2	0.244	0.06	4.23
alpha3	0.0252	2.68	0.00942
beta3	-1.57	-13.8	0.114

Table D.6: Estimation result for Model 6 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0010 Root MSE = 1.63			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.00257	0.12	0.02085
beta	-0.216	-0.04	5.90
alpha2	0.00818	0.16	0.0514
beta2	0.245	0.06	4.24

Table D.7: Estimation result for Model 7 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0043 Root MSE = 1.62			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha2	0.00819	0.16	0.0513
beta2	0.244	0.06	4.23
alpha3	0.0252	2.68	0.00942
beta3	-1.57	-13.8	0.114

Table D.8: Estimation result for Model 8 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0028 Root MSE = 1.62			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.00256	0.12	0.02082
beta	-0.215	-0.04	5.89
alpha3	0.0252	2.68	0.00943
beta3	-1.57	-13.8	0.114

Table D.9: Estimation result for Model 9 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0043 Root MSE = 1.62			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.00256	0.12	0.0208004
beta	-0.215	-0.04	5.89
alpha2	0.00266	2.36	0.00113
alpha3	0.0252	2.68	0.00942
beta3	-1.57	-13.8	0.114

Table D.10: Estimation result for Model 10 for acceleration

No. of observation = 2894 Adjusted R-squared = 0.0018 Root MSE = 1.62			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	0.00256	0.12	0.02083
beta	-0.215	-0.04	5.89
alpha2	0.00818	0.16	0.0514
beta2	0.245	0.06	4.24
alpha3	0.000595	1.86	0.000319

Deceleration Models

Table D.11: Estimation result for Model 1 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.0136 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.00127	-0.17	0.00760
beta	-0.137	-0.03	4.18
alpha2	0	-0.45	0
beta2	12.0	9.66	1.24
alpha3	-0.00000624	-0.66	0.00000948
beta3	5.42	5.42	0.999

Table D.12: Estimation result for Model 2 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.0055 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.00105	-1.73	0.000603
alpha2	-0.00301	-1.87	0.00161
alpha3	-0.00704	-3.64	0.00193

Table D.13: Estimation result for Model 3 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.223 Root MSE = 1.22			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.214	-18.6	0.0115
alpha2	-0.209	-12.19	0.0172
alpha3	-0.229	-17.4	0.0132

Table D.14: Estimation result for Model 4 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.0065 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.000240	-1.69	0.000142
alpha2	-0.000856	-1.98	0.000433
alpha3	-0.00217	-3.99	0.000543

Table D.15: Estimation result for Model 5 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.0139 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.000240	-1.70	0.000141
alpha2	0	-0.45	0
beta2	12.0	9.66	1.24
alpha3	-0.00000624	-0.66	0.00000948
beta3	5.42	5.42	0.999

Table D.16: Estimation result for Model 6 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.0055 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.00128	-0.17	0.00766
beta	-0.1403	-0.03	4.18
alpha2	0	-0.45	0
beta2	12.0	9.63	1.24

Table D.17: Estimation result for Model 7 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.0133 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha2	0	-0.45	0
beta2	12.0	9.66	1.24
alpha3	-0.00000626	-0.66	0.00000950
beta3	5.42	5.42	0.999

Table D.18: Estimation result for Model 8 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.00850 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.00127	-0.17	0.00762
beta	-0.137	-0.03	4.19
alpha3	-0.00000623	-0.66	0.00000948
beta3	5.42	5.41	1.0013

Table D.19: Estimation result for Model 9 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.00940 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.00127	-0.17	0.00761
beta	-0.137	-0.03	4.19
alpha2	-0.000855	-1.98	0.000432
alpha3	-0.00000623	-0.66	0.00000948
beta3	5.42	5.41	1.00089

Table D.20: Estimation result for Model 10 for deceleration

No. of observation = 3024 Adjusted R-squared = 0.0104 Root MSE = 1.38			
Co-efficient	**Value**	**t-stat**	**Std. error**
alpha	-0.00123	-0.17	0.00758
beta	-0.135	-0.03	4.19
alpha2	0	-0.45	0
beta2	12.0	9.65	1.24
alpha3	-0.00216	-4.00	0.000542