Work Zone Characteristics in Microscopic Acceleration Modeling: Calibration and Numerical Analysis

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Dedication

I dedicate this thesis and all of my achievements to my loving and supporting family and all those who helped me bring this research study to fruition.

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Abstract

Work Zone Characteristics in Microscopic Acceleration Modeling: Calibration and Numerical Analysis

The essential need to maintain roadway structures, makes encountering work zones an inevitable part of today's driving. Presence of work zones can impact the traffic flow characteristics in the macroscopic and the microscopic levels. The corresponding changes in traffic dynamics directly affect the mobility and the safety in work zone areas. As the work zone changes in terms of layout and design, the driver behavior changes. Accordingly, a closer look into driver's interaction with work zones geometrics and activity features may be helpful. The objective of this study is to examine the longitudinal characteristics of driver behavior in different work zone conditions using a driving simulator. For this purpose, a detailed literature review motivated the examination of work zone related factors. The corresponding 3 exogenous variables are the work zone length, the barrier type (between the activity area and the passing traffic) and the level of activity. 8 different scenarios were designed by changing these 3 variables in the STISIM driving simulator. After implementing the driving tests, the output trajectory data is recorded for each subject driver (i.e., participant).

In order to quantify the driver's perception of the surrounding environment (i.e., work zone layout and activity) and his/her judgment-execution process, a prospect-theory (PT)

based acceleration model is adopted in this study. This model translates a subjective utility-maximization framework to longitudinal acceleration maneuvering. In other words, the driver's longitudinal behavior is modeled using a microscopic traffic acceleration model. The parameters of the corresponding PT model are calibrated using genetic algorithm. Exploring the differences in parameter values for different scenarios helps understanding the impacts that one or a combination of external factors may have on longitudinal driver behavior in work zone areas. Initial analysis of the driver's acceleration behavior shows that drivers tend to attain higher average speeds and shorter average space headways in work zone areas characterized by jersey barriers. It also showed that drivers attain higher speeds at long stretches of work zones and in low-level activity work zones. After calibrating the parameters of the above mentioned PT model for each scenario, a series of multivariate analysis of variance (MANOVA) tests were conducted to examine the validity of the assumption that differences observed in the calibrated parameters are caused by the external variables (i.e., work zone characteristics) rather than inter-driver heterogeneity. The test results showed that different parameters are sensitive to different work zone characteristics. The γ parameter (indicator of the intensity of the driver's reaction to external factors) changes most when the level of activity changes which means drivers react to changes in level of activity more extremely. Driver's evaluation of the relative losses in velocity with respect to the relative gains (i.e., parameter W_m) is more sensitive to the changes in barrier type and activity level indicating more or less risk averseness. Finally, the drivers uncertainty about the leader's

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CHAPTER 1: INTRODUCTION AND MOTIVATION

1.1 Introduction

Using motor powered vehicles on roadways started during the industrial revolution of the late 1700s; however, the Ford Model *T*, an automobile that was produced by Henry Ford's Ford Motor Company from October 1,1908 to May 27,1927 is generally regarded as the first affordable automobile; this car allowed a personal motorized mean of transportation to the common middle-class Americans. The Model T was the first automobile mass-produced on moving assembly lines with completely interchangeable parts. The United States saw large increases in both motorization and urbanization starting in the 1920s. This led to migration of the population from the densely populated rural areas into the outlying suburbs and this was the beginning of modern peak-hour patterns. The following sections give a brief description of how the inevitablity of road maintenance and the resulting problems and expenses necessitate the need for further studying of work zones, their characteristics and the safety and mobility of the corresponding roadway sections.

1.1.1. Road Maintenance

According to a report from the American Road & Transportation Builders Association, between 75 and 80 percent of 1001 Americans polled in a survey said that they would rather have “safe, efficient and well-maintained transportation infrastructure” over a cell phone or cable TV. 74 percent of them agreed on “investing in transportation infrastructure should be a core function of the federal government.” The following figure demonstrates the average annual expenses of road maintenance in US in 2006, 2007 and 2008. This figure indicates that approximately $16 billion a year is spent on road construction and maintenance.(“FHWA Highway Statistics ”, 2008)

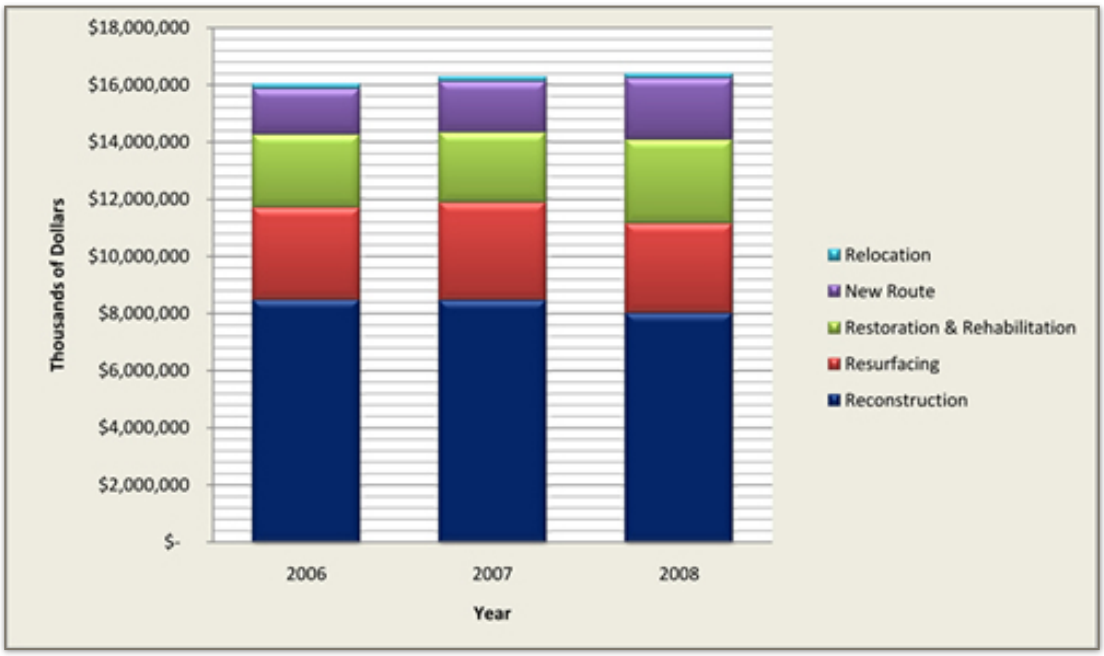

Figure 1.1 Work Zone activity types and maintenance expenses (Highway Statistics 2008, US Department of Transportation, Federal Highway Administration)

The lack of mobility in work zone areas causes a significant part of road congestion which results in excess delay and fuel consumption. Americans lost 5.5 billion hours in 2011 sitting in traffic jams (Schrank et al., 2012). Nearly 24% of non-recurring freeway delay, or about 482 million hours, is attributed to work zones. ("National Strategy to Reduce Congestion on America's Transportation Network", 2006) Figure 1.2 demonstrates the contributing sources of total road congestions for US. It is important to note that the contributing factors to congestion differ between rural and urban roads.

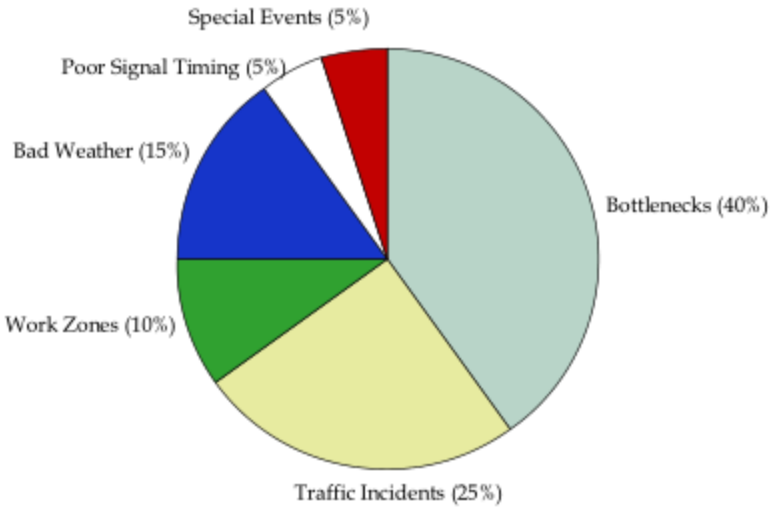

Figure 1.2 Sources of congestion, (Source: "Traffic Congestion and Reliability: Linking Solutions to Problems," prepared by Cambridge Systematics, Inc. for the Federal Highway Administration, Office of Operations, Washington, D.C., July 2004.)

As for the fuel consumption (according to the 2012 urban mobility report), the annual fuel loss in 2011 in 498 US urban areas due to work zone congestion is estimated to be $1.0179 billion (2.9*0.10*3.51). $3.51 is the average diesel price for 2011; $2.91 billion is the total fuel loss in urban areas and 0.10 is the percentage of the contribution to congestion for work zones (see figure 1.2). It is important to note that the average gas price can be higher, and the wasted fuel data is limited to urban areas; therefore, $1.0179 billion is a conservative estimate (average gas price for 2011 from http:// fuelgaugereport.aaa.com). Even though emission/fuel consumption and mobility are among the key concerns, work zone safety remains a priority for transportation engineers. In 2010, based on National Work Zone Safety Information Clearinghouse Work Zone Fatalities, FARS Data, and Traffic Safety Facts, There were 87,606 crashes in work

zones. 0.6% were fatal crashes, 30% were injury crashes, and 69% were property damage only crashes. (“Facts and Statistics - Work Zone Injuries and Fatalities”, 2010). 61 workers were killed while directing or flagging traffic. Ten workers were killed by drunk drivers. Workers were fatally struck 101 times by a vehicle or mobile equipment that was backing up. This is 1.6% of the total number of roadway crashes (5,419,345) in 2010. There were 514 fatal motor vehicle crashes in work zones, resulting in 576 fatalities. These 576 fatalities equate to one work zone fatality every 15 hours (1.6 a day). There were 37,476 injuries in work zones. This equates to one work zone injury every 14 minutes (96 a day), or about four people injured every hour. In addition, the fatal occupational injuries statistics presented in table 1.1 demonstrates that on average, 2.24% of fatal occupational incidents over years 2003 to 2010 has happened to road construction workers.

Table 1.1 Fatal occupational injuries at road construction sites and at all sites, 2003–2010. (Source: U.S. Department of Labor, Bureau of Labor Statistics, in cooperation with state, New York City, District of Columbia, and federal agencies, Census of Fatal Occupational Injuries.)

Year	2003	2004	2005	2006	2007	2008	2009	2010	2003–2010
Road construction	110	119	165	139	106	101	116	106	962
All sites	5,575	5,764	5,734	5,840	5,657	5,214	4,551	4,690	43,025
Road construction as a percentage of all fatal occupational injuries	2.0	2.1	2.9	2.4	1.9	1.9	2.5	2.3	2.2

In a National Cooperative Highway Research Program (NCHRP) report, collision types were studied based on activity time and lane closure for 64 work zones. The following table represents the results of a study on collision types for 64 work zones:

Table 1.2 Work zone crash data for 64 projects in California, North Carolina, Ohio, and Washington (source: NCHRP Report 627, "Traffic Safety Evaluation of Nighttime and Daytime Work Zones)

Percentage of Crashes by Collision Type for the 17,228 Crashes Studied						
Type of Collision	**Night Work**			**Day Work**		
	Active Work With Lane Closures	**Active Work Without Lane Closures**	**No Active Work or Lane Closures**	**Active Work With Lane Closures**	**Active Work Without Lane Closures**	**No Active Work or Lane Closures**
Rear-End Crashes	38.4%	33.6%	26%	46.9%	54.4%	48.7%
Sideswipe Collisions	15.8%	21%	15%	13.6%	14.8%	14.8%
Fixed-Object Collisions	22.8%	21%	31.9%	20.3%	10.3%	15.9%
All Other Collision Types	23.1%	24.4%	25.2%	19.2%	20.6%	14.1%

Based on the information presented in the table above, a significant proportion of work zone collisions is related to error in longitudinal acceleration (Rear-End-Collision) and lane changing (Sideswipe Collisions) driving behavior. It is also notable that rear-end collisions occur more frequently than sideswipe collisions in work zones with and without lane closure and during day and night time. Given the corresponding problem and aforementioned statistics on work zone injuries and fatalities, several agencies

including The Federal Highway Administration (FHWA) have taken measures to improve the safety and the mobility in work zones.

1.1.2. FHWA Measures to Improve Work Zone Safety and Mobility

Dissatisfactory statistics on work zone congestion, delay, and safety are continually motivating new approaches to improve traffic operations in and around work zones. Unavoidably, the increasing need to repair and maintain rapidly deteriorating infrastructure grows the need for setting up work zones. The evaluation of the work zones began with the collection of speed and volume through video data. The data were assessed to determine the impact of the work zone on microscopic and macroscopic driver behavior in microscopic and macroscopic. Encountering work zones often violates driver's expectation of the forthcoming roadway conditions. The differences in spatial location and also temporal duration of work zones makes these encounters more unpredictable. Hence, driver's Driving through work zones. This clearly elevates the risk of collision (Wang et al., 1996). In 2006, the US National Highway Traffic Safety Administration (NHTSA, 2008) recorded over 1000 fatal incidents in work zones. Other safety related studies also emphasize on elevated risk of collision in work zones. Council et al. (2000) reported a 21.5% higher total crash rate inside the work zones compared to a pre-work area. They also found that factors of duration and length most systematically contribute to the elevated risk. Similar trends have also been reported in earlier studies. Liste et al. (1978) recorded an increase of 119% in crash rate within the studied work

zones. Rouphail et al. (1988) reported an 88% higher crash rate at one long-term work area compared to a pre-work zone period. Based on these studies, It is evident that the spatial configuration and temporal persistence of the work zones are among the leading contributors to work zone safety. Work zones impact driver behavior in several aspects. Drivers tend to change their driving behavior when encountering a construction zone. These changes are measurable in terms of speed, acceleration, lane position and merging to the adjacent lane because of the lane closure and this behavior varies with different configurations of a work zone and general safety and management measures taken in work zones. These measures fall into four categories (Michelle L. Reyes, Sameer A. Khan, 2010) : speed regulation, path regulation, visibility and conspicuity and general work zone interventions. Establishing speed limits in work zones is the key to driver and worker safety. Different technologies and methods can be utilized to enforce speed management policies in work zones. Automated enforcement such as use of photo radar speed cameras, presence of uniformed law enforcement officers, speed advisory systems and variable speed limit systems are among speed regulation strategies for work zones. Path regulation measures are a mean to control driver's merging and lane changing behavior. The design pavement markings, the choice of channelizing devices and the length of taper, transition and termination areas of the work zones are the contributing factors to effective path regulation. Several studies have investigated the effects of different path regulations on work zone traffic mobility and safety. Visibility of work zone elements is an important part of preventing work zone incidents. High visibility apparels, activity area planning, proper separation of traffic and work activities, proper

lighting for nighttime activities and use of special devices such as rumble stripes and intrusion alarms are some of the considerations in this matter. To address all these issues, a safety specialist is needed to make sure all the safety regulations required in federal agency manuals such as Manual on Uniform Traffic Control Devices (MUTCD) and Occupational Safety and Health Administration (OSHA) are met. The above mentioned measures can be effectively applied only with proper and continuous training of drivers, workers and other involved practitioners. Therefore, FHWA has developed the National Highway Work Zone Safety Program (NHWZSP) and offers several training programs, research services, webinars and etc for the community (http://safety.fhwa.dot.gov/wz/). Given the suggested means generally taken to improve the safety and mobility in work zones, it may be helpful to present a background on driver behavior in work zones and corresponding configurations.

1.2. Background on Work Zone and Driving Behavior

Work zone configuration characteristics that can affect driving behavior and work zone capacity include total number of lanes, number of lanes left open through the work zone, and geometry such as: grade, presence of horizontal or vertical curve, lane width, and shoulder type and width (Maze,T.H.,S.D. Schrock, and A. Kamyab, 2005). Work zone configuration also refers to the location of the closed lanes (i.e., closure of rightmost lanes versus closure of leftmost lanes). (Al-Kaisy, A. F., and Hall, F. L., 2002) studied this factor using Burlington Bay Skyway data, Results suggested a 6% higher capacities for rightmost lane closures versus leftmost lane closures. Necessity of change in driver's

speed and merging behavior in the work zone area can directly and dramatically impact the work zone capacity. Drivers tend to attain lower speeds at the times that work zone activity is closer to the open lane even at the even when there is a concrete barrier between the driver and the construction activity (Memmott, J.L. and C.L. Dudek, 1982). In terms of the location of merging point and the corresponding enforcement, merging upstream from the taper point of a lane closure increases capacity more than late merging; however, drivers not following the expected merge discipline skip to the head of the queue and force themselves into the traffic stream, creating a crash risk and turbulence and reducing the efficiency gained through an early merge. Locating enforcement personnel can improve early merge behavior (Kamyab, A. , McDonald, T., B. Storm, and M.E. Anderson-Wilk, 2003). (Heaslip, 2007) found that driver behavior in work zones and concepts such as driver accommodation, aggression, familiarity, increased cognitive loads, and adaptability are not adequately represented. Moreover, it was reported that in traditional car following behavior and traffic macrosimualtion do not accurately represent work zones. (Heaslip, 2007) found that driver behavior in work zones and concepts such as driver accommodation, aggression, familiarity, increased cognitive loads, and adaptability are not adequately represented. Moreover, it was reported that in traditional car following behavior and traffic macrosimualtion do not accurately represent work zones. These conclusions led to the formulation of an algorithm to represent forced merges in work zones. The following issues were focused on:

- lane closure/lane transition practices

- portable changeable (variable) message signing practices
- channelization practices (path guidance)
- delineation of crossovers/alternate travel paths
- temporary pavement markings

Data collection was conducted on a long-term bridge replacement project along Interstate 91 in Greenfield, Massachusetts, where there was a full lane closure on the roadway. Speed and video data were collected over a four month period to observe the effects of the work zone features implemented and assessed the traffic patterns, vehicular movements, and driver behavior in the work zone area.(Michelle L. Reyes, Sameer A. Khan, 2010) performed 6 unique experimental drives developed using the NADS Interactive Scenario Authoring Tool (ISAT). The authors studied the effect of barrier types, lateral buffer and level of activity in work zone on driver behavior. The results showed that participants drove the fastest and with less variability in work zones with concrete barriers. Drums and channelizers affected driving performance differently depending on the work zone conditions. For some combinations of conditions, the 4ft lateral buffer provided the expected benefit of reduced speed variability. However, average speed across all four combinations of age and gender were more similar to one another without the buffer, particularly for the drum and channelizer work zones. In addition, areas of high work zone activity led to slower average speed and increased speed variability compared to low activity areas. The results also suggested that work zones with lengthy longitudinal buffers or intermittent areas of work activity have the

potential to increase crash risk by creating more opportunities for large speed differentials to develop. Voorrips (2013), studied four determinants which are specific to work zones and also can be influenced by authorities and contractors. These determinants are:

- lane width
- speed limit
- contra flow/Reverse curve
- channelizing device

He used an unmanned helicopter to collect trajectory data in three different work zone locations. The author then investigated headway distributions, speed distributions, and lane occupation distributions while changing the above mentioned determinants. He found that reduced lane width in combination with a barrier close to the carriageway (as a channelizing device) instead of the normal guardrail results in capacity reduction. He also concluded that reverse curve can be responsible for an additional decrease in capacity of the work zones.

1.3. Research Objectives

Given the motivation and the research work mentioned earlier, the objective in this study is to assess construction zone's impact on the surrounding traffic in terms of drivers' lane changing and acceleration behavior using a driving simulator. For this

purpose, 8 specific scenarios were designed, each representing a different work zone in terms of length, level of activity distribution and the barrier type used for separation of "under construction" and "in service lanes". 40 driving experiments were performed on 25 participants in order to investigate the change pattern in their lane changing and acceleration behavior. The data obtained from the driving experiments were used to calibrate the prospect theory based (PT) acceleration model. The model includes 8 parameters which are indicators of driver's cognitive characteristics. The 8 model parameters are defined as follows:

- Parameter γ : It defines the shape of the asymptotics of the generalized PT utility; one may mention that the more extreme the driver's reaction to external factors, the higher the estimated value of γ is.

- Parameter W_m : It represents the weight of the prospect theory's relative losses in speed with respect to gains associated with a change in velocity.

- Parameter W_c : It reflects an individual's subjective sensitivity to the losses that are caused by a potential rear-end collision.

- Parameter $\tau_{\max}$: It reflects the maximum anticipation time horizon

- Parameter α : It reflects the subject driver's uncertainty about the leading vehicle's speed, the more uncertain and defensive the driver is, the higher the values of α are.

- Parameter β : It is the logit uncertainty parameter which reflects the sensitivity to the PT utility.

- Parameter τ_{corr} : It represents the correlation time of intra-driver variability. The smaller the τ_{corr} is, the greater the fluctuations in acceleration choices are.

- Parameter RT: It defines the driver's reaction time.

In order to estimate the parameter values for a model that may optimally present the driver acceleration behavior in work zone areas, Genetic Algorithm is employed. First a potential value is assigned to each parameter. These values are obtained from Hamdar et al. (2008). Then, driver's acceleration behavior is anticipated by the calibrated model and the result of this anticipation is compared to the behavior of drivers in the driver simulator through a fitness function. In fact, the fitness function evaluates the error of model's anticipation by comparing the anticipated velocity of the driver and the driver's actual velocity in the driving simulator vehicle. Genetic algorithm evolves the initial set of parameter values toward a set of more optimal solutions in each repetition of its cycle until the error reaches an acceptance criteria. The final parameter values are obtained as calibrated model parameters. Based on the calibration results, the model performance and the features of longitudinal driving behavior are evaluated through statistical tests. The conclusions are made based on statistical results and the impact of different work zone characteristics are assessed accordingly.

In summary, after studying the available relevant statistical data in work zone areas and a thorough investigation in the previous work-zone related researches, an experimental set-up including 8 different scenarios is designed to simulate a real-life work zone driving experience in a driving simulator system. The trajectory data collected from the participants is used to calibrate an acceleration model for each of the 8 different scenarios. Observing and evaluating the differences in parameter values through statistical tests leads to the understanding of impacts of the selected work zone characteristics on driver behavior.

1.4. Thesis Organization

Based on the thesis objectives and the background studies presented in section 1.2, the three major contributing factors considered in this study, include the work zone length, the level of activity inside the work zone and the barrier type used for separating the closed lane from the lanes in service. The study starts by reviewing some introductory concepts related to microscopic traffic modeling and simulation, the corresponding model's evolution over time and their yet to be studied drawbacks and limitation in chapter 2. Chapter 3 presents an introduction on the PT based model and its features. The framing and the evaluation steps of the model are then discussed and the corresponding modeling characteristics are discussed using basic sensitivity analysis. Chapter 4 describes in detail the data collection methods and the corresponding experimental set-ups. 8 differently designed scenarios are created using the STISIM driver simulator

language to capture the impact of various work-zone characteristics on driving behaviors. This chapter continues with the initial analysis of simulator output results. The initial analysis looks into the measures of average speed, average time headway and average space headway and performs ANOVA test to capture correlation between different sources of variation and their contribution to the change in the mean values of measurements. The general impacts of work zone characteristics' variations on driver behavior are presented in terms of speed, time and space headway. In Chapter 5, the calibration process of the model parameters is explained and the Genetic Algorithm (GA) is implemented through the definition of the "genes" and the fitness function. Next, the calibration results are presented in detail followed by the corresponding MANOVA test. Finally, careful observation of the results and different evaluation approaches has led to interesting findings which are discussed comprehensively in several sections of this chapter. This thesis is then concluded in chapter 6 by a summary of the corresponding research findings, contributions and the possible future needs.

CHAPTER 2: LITERATURE REVIEW

As mentioned in chapter 1, there has been several methods to analyze driver behavior and the corresponding safety implications in work zones. To quantify behavioral pattern in a systematic pattern, one may need to utilize microscopic traffic models. In this chapter, a review on such microscopic models is presented. Microscopic traffic simulation does not consider macroscopic measures which are aggregate physical traffic flow characteristics like occupancy (percent of time a point on the road is occupied by vehicles), rates of flow (vehicles per unit time), density (vehicles per unit distance), and average speed (distance per unit time). The microscopic approach to study traffic flow focuses on the individual characteristics of each vehicle's movement under different traffic conditions. Microscopic models may be classified as acceleration models, lane changing models, merging models and gap acceptance models. The focus in this chapter will be on the acceleration models (representative of the longitudinal driving movement) and the lane changing models (representative of the lateral driving movement). With noticeable advances in data acquisition technologies and computational processing power, microscopic models have been developed and widely applied in traffic engineering e.g. for capacity analysis, traffic impact studies, junction design, accident analysis, network analysis and ITS throughout the past decades.

2.1. Acceleration Models

Acceleration models were the first microscopic models developed for driver behavior. An acceleration model studies the driver/vehicle movement with respect to the leading vehicle in the same lane. The following vehicle's action is usually described through its acceleration. Acceleration models can describe driver's behavior not only when following a leading vehicle but also in other regimes such as free driving (unconstrained) and emergency deceleration. Although numerous models have been proposed since the early investigations on acceleration models, such models may be classified into four general categories. Gazis-Herman-Rothery models (GHR) are also referred to as the General Motors (GM) or stimulus-response models. These models state that the following vehicle's acceleration response is proportional to a stimulus. The stimulus may be the speed of the follower, the speed difference between follower and leader or the space headway (Brackstone and McDonald, 1998). There are many suggested forms of the stimulus and the proportionality terms (called the sensitivity terms). One suggested expression is offered next.

$$a_n(t) = \alpha . v_n^{\beta}(t) . \frac{(v_{n-1}(t-T) - v_n(t-T))}{(x_{n-1}(t-T) - x_n(t-T))^{\gamma}} \qquad \textbf{(Equation 1.1)}$$

$\alpha>0$, β and γ are model parameters that control the proportionalities.

a_n Acceleration, vehicle *n,* [m/s^2]

x_n Position, vehicle *n,* [*m*]

v_n Speed, vehicle *n,* [m / s]

L_{n-1} Length, vehicle *n-1,* [*m*]

T Reaction time, [*s*]

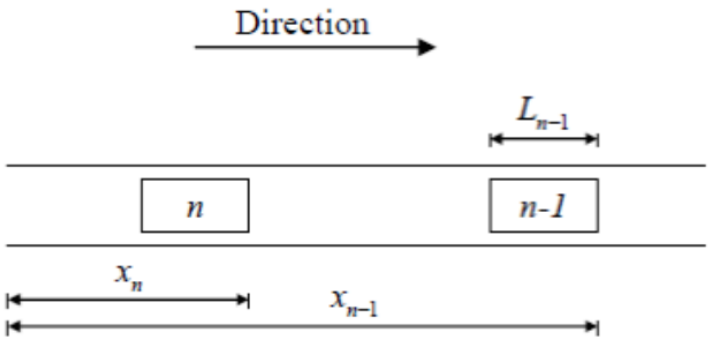

Figure 2.1 A typical acceleration model formulation

Some of the suggested problems in the GHR models are related to the corresponding assumptions. Looking at the formulation above, any arbitrary small change in the relative speed can affect the follower's acceleration. Such behavior may not be observed in real life driving since drivers react to changes in relative speed which is above a certain threshold. These GHR models are also based on the assumption that no matter how large

the space headway between the two following vehicles is, the follower will react to the leader's speed changes. Another nonrealistic assumption made in these types of models is that the following vehicles' acceleration response disappears (becomes zero) as soon as the relative speed becomes zero. These flaws in GHR models are improved by incorporating additional regimes. Helly's linear model constitutes another category on its own. This model can be considered an improved version of the GHR models through the introduction of anticipation and heterogeneity into driver's car following behavior. In addition to the GHR models, safety-distance or collision avoidance models describe the follower's behavior assuming that the following vehicle always attempts to keep a safe distance/speed to the leading vehicle. Even though the models stated earlier had some success representing driving behavior observed in real-life conditions, they did not take into consideration the perception and the psychological characteristics of the drivers. To that end, Michaels (1963) developed the psycho-physical models. The logic behind psycho-physical models is that the following vehicle's driver does not react to the spacing or speed changes until such changes reach a certain perceived threshold. The reaction zones are represented on a relative speed/space diagram offered in the following figure.

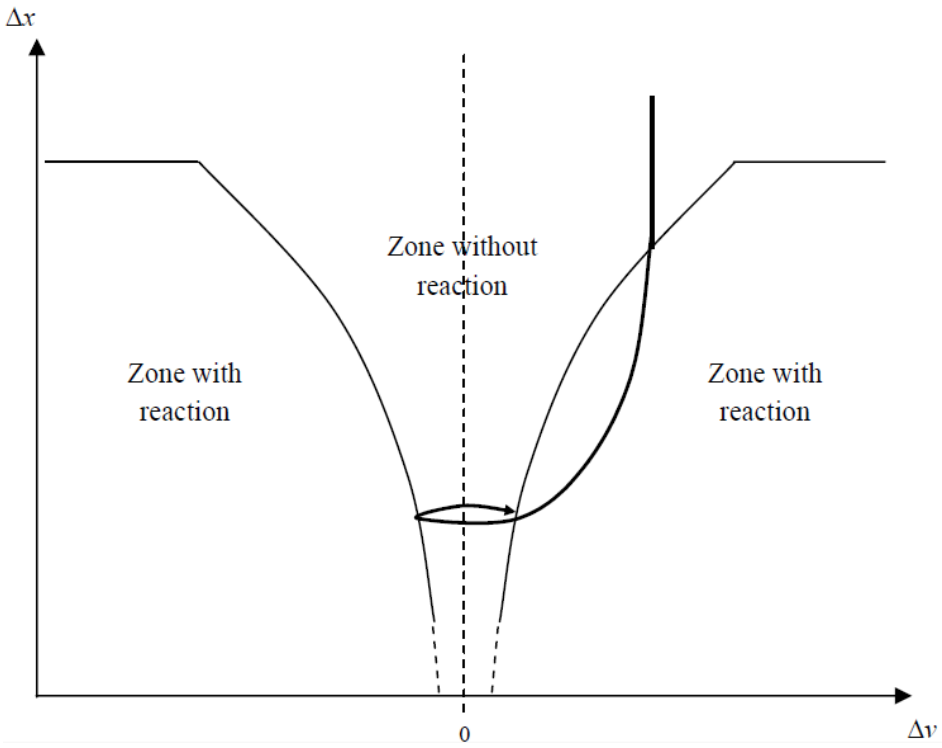

Figure 2.2 A psycho-physical car-following model.

These models were further developed by Wiedemann (1974) and are adopted in the widely used VISSIM traffic software. Further models are developed over the years to improve the accuracy in representing. For example, the fuzzy logic car-following model was developed by the Transportation Research Group (TRG) at the University of Southampton (Wu et al., 2000) to take into account drivers' perception of different stimuli.

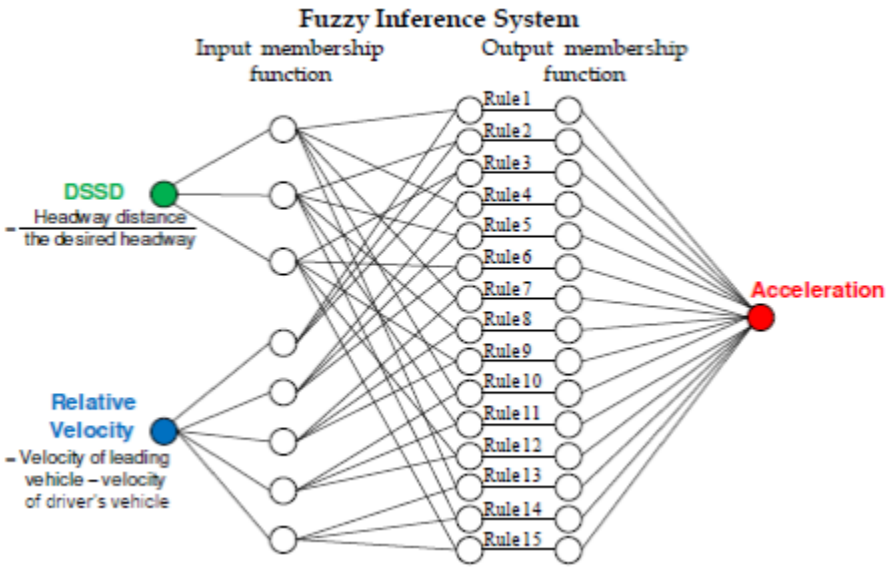

Figure 2.3 Example of Structure of Fuzzy inference model for Fuzzy logic car-following models. (source: Toshihisa Sato and Motoyuki Akamatsu (2012))

The relation between a stimulus and a response is represented by a Fuzzy inference system. This system has four layers. The first layer is the input (state) layer which is a continuous state variable. The traffic state can be defined by either the space headway or relative speed in most of the acceleration models. The second layer is the input membership function layer or the fuzzy membership layer. In this layer, states are mapped to linguistic terms. Based on the scalar value for sate input they are fuzzified into terms such as "High DSSD" or "relative speed is low". Fuzzy membership functions can be Gaussian, triangular or trapezoidal. Each state input variable belongs to more than one fuzzy discrete set for more accurate transformation. Each combination of these discrete fuzzy sets will associate with one of the rules in the next layer. The third layer is the rules

layer which determines how previously defined fuzzy sets are connected to output membership functions. Output membership functions (discrete action layer) is the fourth layer specifying what would be the drivers next action (acceleration or deceleration) based on his current traffic state. In addition to the longitudinal acceleration models, lateral lane-changing models can also capture driving behavioral patterns especially in work-zones. The first frame used for presenting a microscopic model for drivers lane changing behavior was proposed by Gipps (1986). This model considered three major factors: necessity, desirability and safety in prioritizing drivers's goals in a lane selection decision. The main possible limitation of the Gipps' lane changing model is related to the deterministic rule-based logic adopted in capturing driving behavior. In other words, Gipps did not take into account inconsistency and non-homogeneity in driver behavior when more than one lane is acceptable. Gipps' framework was implemented in a number of future microscopic traffic softwares. In CORSIM Halati et al. (1997) classified lane changing as mandatory lane changing (MLC) and discretionary lane changing (DLC) and quantified the drivers' motivation to perform DLC in terms of speed and headway. In MITSIM, Yang and Koutsopoulos (1996), introduced a probabilistic approach to model lane selection in case of conflicting goals. This model assumes that drivers' mandatory lane change is due to four externally imposed conditions. A restricted used lane, compulsory traffic signs, a lane blockage and required change of passage as the next step to arrive at destination. If there are more than one of these conditions present, the problem is resolved using the utility theory. Discretionary lane changes are modeled based on drivers desire to reach the desired speed and his /her gap acceptance in the

target lane. Kita (1993) also utilized logit theory through a model to estimate a gap acceptance model for merging behavior at expressway on-ramps. Hidas and Behbahanizadeh (1998) changed the definition of drivers goals for DLC in their SITRAS model and also introduced the cooperative lane changing in MLC. Their new definition added joining the shorter queue to the faster speed as drivers motivations for discretely changing the lanes. In other words, drivers would consider joining the lane with fewer vehicle as well as joining the lane which would provide a faster speed. The second new addition in this model is cooperative lane changing. The lane changing maneuver is seen as a mutual interaction between the subject vehicle and the follower in the target lane. The subject vehicle is able to change lane if only the follower is willing to provide the accepted gap. This willingness is defined as a function of the follower's aggressiveness. This model, despite the added feature, also fails to capture the inconsistency and non-homogeneity of driver behavior over time. Ahmed (1999) used a discrete choice framework to model lane changing decisions estimating the gap acceptance and lane selection parameters (figure 2.4). For non-mandatory lane changing, a driver makes his/ her decision to change lanes based on the evaluation of his/her traffic condition in the current lane. Dissatisfactory condition leads the driver to change lane. The lane utility is a function of relative speed of the follower and the leader vehicles in adjacent lanes both to the current and the desired speed of the subject vehicle.

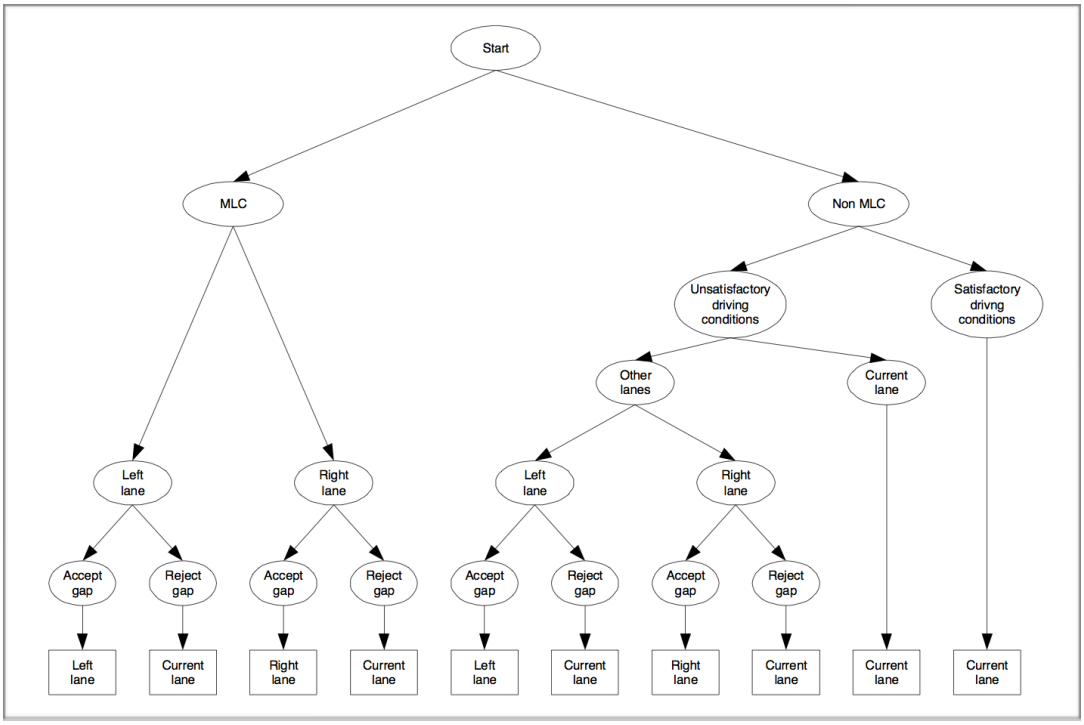

Figure 2.4 Structure of the lane changing model proposed by Ahmed (1999)

Wei et al. (2000) pointed out the effect of driver's path plan and passing behavior on lane changing choices. Such integrated model features also proposed by Toledo et al. (2003) allow for trade-offs between MLC and DLC considerations. The model divides the lane-changing process into two steps. The first step consists of choosing the target lane and the second step is deciding if the available gap is acceptable based on driver's critical gap threshold. The variables in Toledo's models represent the vehicle's surrounding condition (neighborhood variables), driver's path plan, driver's network knowledge and experience with the transportation system and individual driving style and capabilities. The model was estimated using detailed trajectory data collected on I-395 Southbound in Arlington, VA. In addition to DLC/MLC lane-changing classifications,

Kugo et al. (2000) used steering behavior data to characterize three different maneuvers: emergency lane change (LCE), normal lane change (LCN), and lane keeping (LKN) and predict lane change intentions in drivers. Steering angle, steering angle velocity, and steering force are the observable variables. They also used the data from a driver simulator as the actual observed driver behavior to compare with the model's simulated behavior. All the previously mentioned models fail to capture the driver's persisting behavior in performing a lane change. In general it is assumed that lane changing decisions are made at discrete points in time independent of the decision made earlier. Given such limitations, the Hidden Markov models (HMM) are suggested. HMMs are statistical models for modeling systems with unobserved hidden states. In case of lane changing, the first step of decision process in Toledo's model is a latent process since the target lane choice is unobservable and only the driver's actual lane-changing action can be observed. Lane selection evolves from state to state generating the unobserved hidden Markov states in the system. In the few proposed applications of HMMs in transportation, the transition between these hidden states can be captured. For example, Figure 2.4 represents a 3-state HMM, where each hidden state (x_i) is connected to one of 4 observable states/actions (y_i) with some probability (b_{ij}). The state transition probabilities (a_{ij}) are the probabilities of moving from one hidden state to another one.

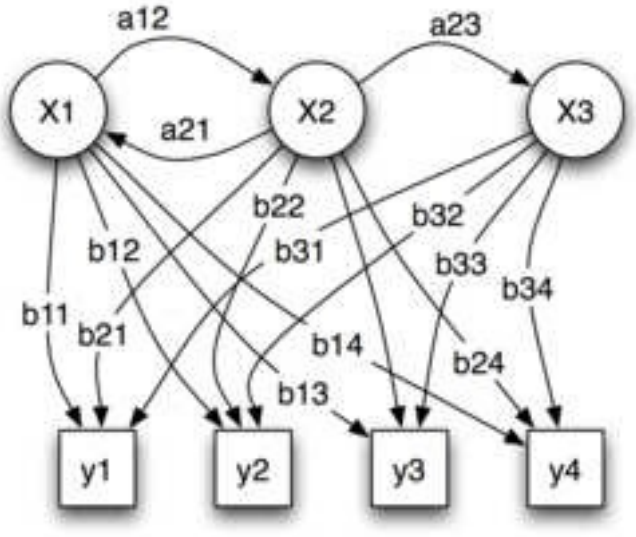

Figure 2.5 A 3-state HMM, with 4 observable states/actions (Source: Wikipedia).

Pentland and Liu (1999) applied HMMs to statistically predict the most likely subsequent sequence of internal states based on drivers' current internal state . They modeled events such as stopping at the next intersection, turning left at the next intersection, turning right at the next intersection, changing lanes, passing the car in front, or doing nothing. They broke down different actions into individual steps that make up the action. These steps are internal hidden states. For the case of lane changing, for instance, the action consists of the following steps: (1) a preliminary centering of the car in the current lane, (2) making sure the adjacent lane is free, (3) steering to initiate the lane change, (4) the change of lane itself, (5) steering to terminate the lane change, and (6) a final re-centering of the car in the new lane. Given the observed pattern of heading and acceleration in the few preparatory steps, HMM can statistically anticipate which of the above actions are being initiated. Pentland and Liu used the data obtained from a

driving simulator to calibrate their HMM. Katz & Toledo (2008) tried to capture state dependency using HMM structures in their lane-changing models using real trajectory data.

In conclusion, different acceleration and lane-changing models have been proposed over the years to capture and understand driver behavior including at work zones. However, such models mainly lack the cognitive-dimension that capture the perception, judgement and execution process adopted by drivers in a dynamic environment. To that end, an alternative formulation framework is adopted in this thesis and is presented in the following chapter.

CHAPTER 3: MODELING FRAMEWORK

3.1. Problem Framing

Studies in human decision making modeling provide a solid base for incorporating driver's behavior and judgment under uncertainty into conventional acceleration models. Such studies started by the Daniel Bernouli's pioneering attempts to measure risk (Bernouli, 1738). This has already led to the classical expected utility theory that was initially introduced by Von Neumann and Morgenstern (1949). However, Inconsistencies between choices actually made by humans and those predicted by the expected value theory were observed (Kahneman and Tversky, 1979; Shafer, 1993). Such inconsistencies motivated the development of Prospect Theory (PT), a behavioral economic theory developed by psychologists Kahneman and Tversky in 1979 as an alternative to expected utility theory. The value function used in this thesis is based on the PT literature. To bring the empirical validity to decision making modeling, prospect theory frames alternatives and attributes as context-dependent changes (gains and losses) relative to an updated reference state which is usually that individual's status quo. In general, most individuals value losses higher than gains of equivalent size and each individual weights expected probabilities of uncertain outcomes with a subjective non-linear probability weight (Prof. dr. G.P. van Wee). These decision making processes are represented by value functions. Value functions are functions that transform an objective quantifiable amount of gain/loss to a subjective perceived gain or loss depending on a person's socio-demographic

characteristics and the conditions during which he/she is making a decision (surrounding environment). A typical value function is illustrated in the following figure.

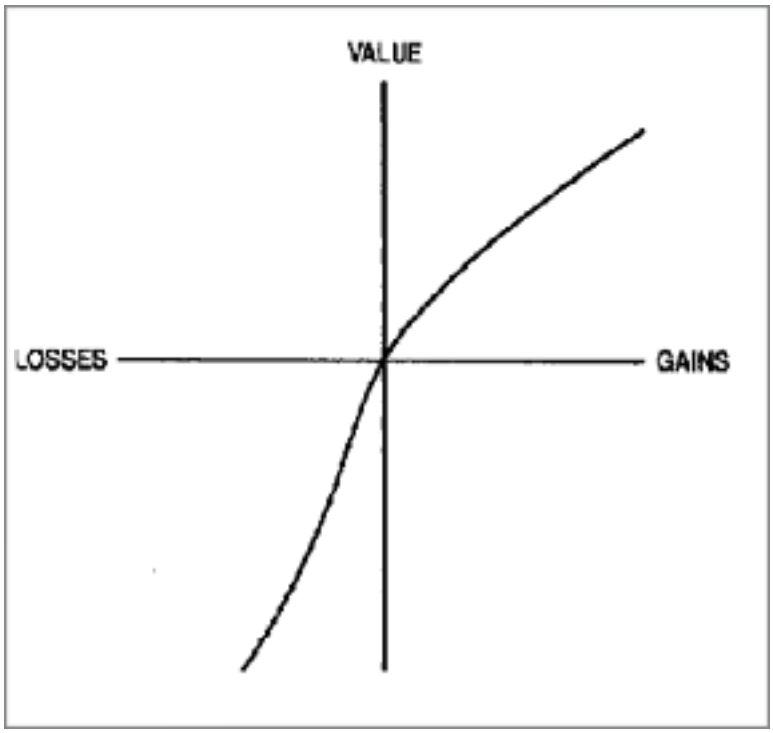

Figure 3.1 A typical value function in prospect theory: the subjective "Value" of a gain/loss to a decision maker versus the corresponding "real" gain or loss (Source: Tversky and Kahneman, 1986).

Three main characteristics of value function may be observed above.

- Loss aversion which is shown by the steeper slope for losses than for gains.
- Gain and loss satiation which is shown by the subsiding sensitivity to increasing gains and losses; and
- Reference level dependence given that the origin is the reference point.

For modeling driving behavior as a continuous cognitive decision making process, a prospect theory based formulation is hypothesized to be feasible in this thesis. While the theory has been utilized for modeling drivers route choice behavior in several studies, It has not been fully investigated in the context of modeling acceleration or lane-changing behavior. The logic behind utilizing a value function for acceleration behavior is related to the driver's objective of minimizing travel time and avoiding involvement in a rear-end collision.In such framing positive change in velocity is considered a gain (i.e., minimizing travel time) while being involved in a rear-end crash is considered a loss. Given that the objective is to look into driver behavioral changes in work zones, the external factors that can be incorporated in this study are the work zone characteristics and traffic condition. Drivers respond to this factors, depends on his perception of the environment and is evaluated based on his subjective needs and targets. This interaction framework is illustrated in figure 3.2.

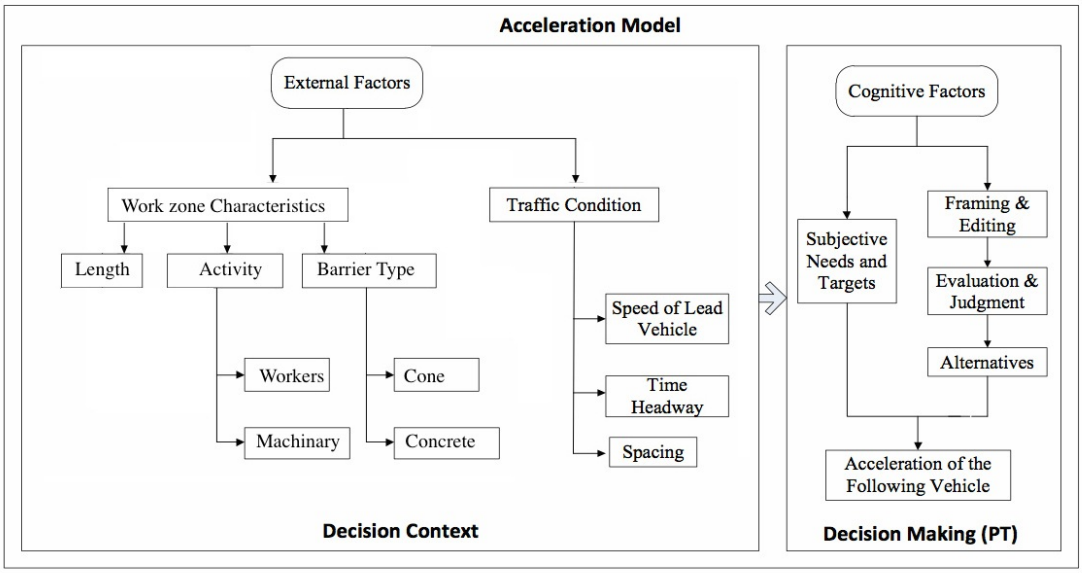

Figure 3.2 Conceptual framework for the acceleration model.

3.2. Formulation Details

The value function to calibrate in this study is an adaptation of the function framed and evaluated by Hamdar et al. (2008) to model driver behavior as a stochastic hazard-based risk-taking process. The value function $U_{pt}(a_n)$ associated with the objective gain/acceleration of vehicle *n (i.e.,* a_n) is defined as follows;

$$U_{PT}(a_n) = \frac{[W_m + (1-W_m)(\tanh(\frac{a_n}{a_0}) + 1)]}{2} \frac{(\frac{a_n}{a_0})}{[1+(\frac{a_n}{a_0})^2]^{\frac{(1-\gamma)}{2}}} \qquad \textbf{Equation 3.1}$$

Where γ and W_m are parameters to be estimated while a_0 is used for normalizing purposes and is set to $1 m/s^2$. This function formulates the prospect value associated with acceleration decision. In order to take into account the probability of crash involvement, another term should be added to form the total objective utility. In other words, the utility associated with an acceleration a_n of vehicle *n* considering the loss that might be caused by a rear-end collision is:

$$U(a_n)=(1-p_{n,i})U_{PT}(a_n)-p_{n,i}w_c k(\Delta v, v) \qquad \textbf{Equation 3.2}$$

where:

$p_{n,i}$ is the probability of colliding with the rear-end bumper of the lead vehicle given that no collision took place in the $(i-1)$th acceleration instance.

W_c is a representative of drivers sensitivity to the accident related losses. This parameter is higher for more conservative drivers and lower for more risk-taking drivers.

k is a seriousness term that may be a function of the speed *v* and relative sped Δv assuming all the drivers experience the same level of seriousness if a rear-end collision occurs. This term is set to be 1 for this study. When the subject (following) driver *n* decides to adopt a candidate acceleration a_n at time *t* during the anticipated time span τ_n, the anticipation time horizon is assumed to be the minimum between the time-to-

collision (i.e., $TTC = S/\Delta v$) and estimated maximum anticipation horizon value $\tau_{\max}$. Δv is also defined as follows:

$$\Delta v_n(t) = v_n(t) - v_{n-1}(t) \qquad \textbf{Equation 3.3}$$

The final term that needs to be introduced in this section is the rear-end collision probability $p_{n,i}$ (Hamdar, 2008). This probability is the same as the probability that the gap between the leading vehicle *n-1* and subject vehicle n is less than zero at time $t + \tau_n$. Such gap is defined by:

$$s_n(t+\tau_n) = y_{n-1}(t+\tau_n) - y_n(t+\tau_n) - l_{n-1} \qquad \textbf{Equation 3.4}$$

Where *l* is the vehicle length; Accordingly the probability of a collision is:

$$t+\tau_n, \text{ i.e., } p_n(t+\tau_n) = P(s_n(t+\tau_n) < 0). \qquad \textbf{Equation 3.5}$$

To calculate this probability some assumptions are made;

1. The leading vehicle's velocity during the anticipated time span follows a normal distribution with a given standard deviation σ and a mean equal to the velocity of the leader (v_{n-1}) at the time *t*. In other words, the estimated velocity of the leader has a probability density function given by:

$$f(v \mid t) = \frac{1}{\sqrt{2\pi}\sigma(v_{n-1})} \exp\left[\frac{-(v - v_{n-1}(t))^2}{2\sigma(v_{n-1})^2}\right] \qquad \textbf{Equation 3.6}$$

2. The leading vehicle and the following vehicle are assumed to have a constant velocity heuristic and a constant-acceleration heuristic during the time interval between t and $t+\tau_n$ respectively. Therefore, the terms from equation 3.4 are calculated accordingly as shown below:

$$y_{n-1}(t+\tau_n) = y_{n-1}(t) + \tau_n v_{n-1}^{est}(t) \qquad \textbf{Equation 3.7}$$

and:

$$y_n(t+\tau_n) = y_n(t) + v_n(t)\tau_n + \frac{1}{2}a_n\tau_n^2 \qquad \textbf{Equation 3.8}$$

The rear end collision probability form the above equation can be written as:

$$p_n(t+\tau_n) = P\left[Z < \frac{\Delta v_n(t)\tau_n + \frac{1}{2}a_n\tau_n^2 - s_n(t)}{\sigma(v_{n-1})\tau_n}\right] = \Phi\left[\frac{\Delta v_n(t)\tau_n + \frac{1}{2}a_n\tau_n^2 - s_n(t)}{\sigma(v_{n-1})\tau_n}\right] \qquad \textbf{Equation 3.9}$$

Equation 3.9 can be transformed to the standardized normal distribution by setting:

$$v_{n-1}^{est}(t) = v_{n-1}(t) + \sigma(v_{n-1})Z \qquad \textbf{Equation 3.10}$$

Where Z is the standardized Gaussian stochastic variable with mean 0 and variance 1; In summary, the driver evaluates candidate accelerations by weighting accumulated gains of increased velocity (reduced travel time) and losses (involvement in an accident and increased travel time) utilizing the total subjective utility $U(a_n)$ represented by equation 3.2.

3.3. Numerical Illustration

In this section, 3 changing conditions associated with work-zones, are hypothesized;

1. Non-challenging conditions (i.e. normal)
2. Moderately challenging conditions (i.e. moderate)
3. Extremely challenging conditions (i.e. extreme)

The following graphs demonstrate the calculated prospect value (Equation 3.1) and total utility (Equation 3.2) for different acceleration candidates using parametric values estimated for each type of the condition defined earlier (further discussed in chapter 5).

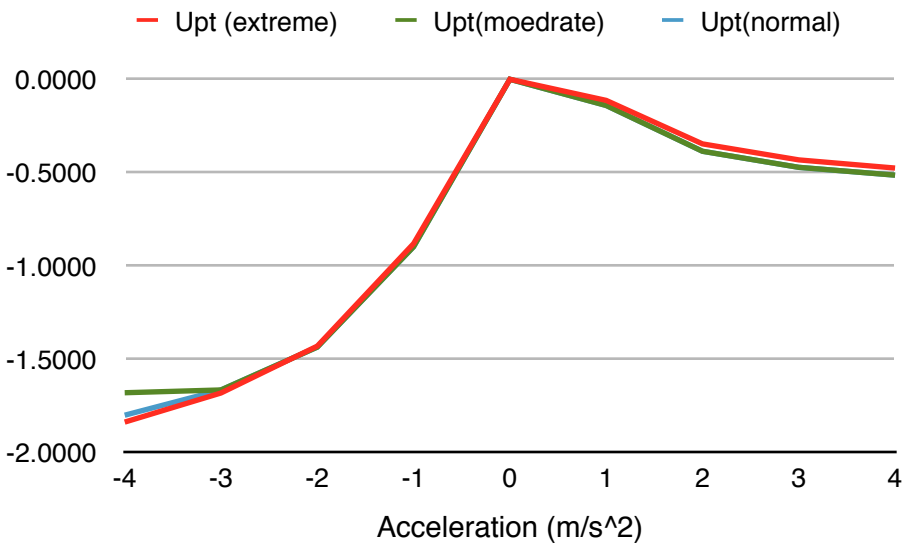

Figure 3.3 Prospect Value (Equation 3.1) for different acceleration candidates with estimated parameters of table (5.2)

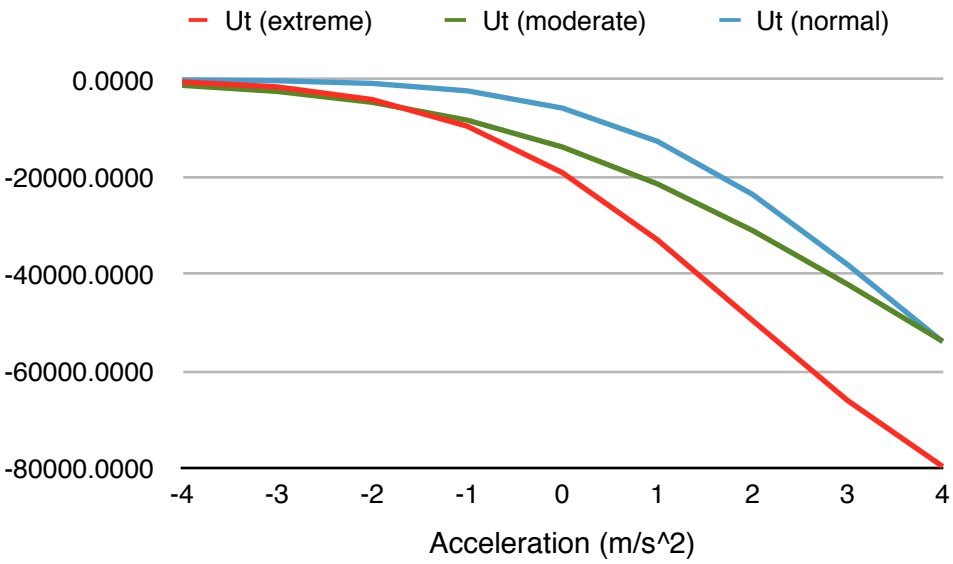

Figure 3.4 Utility (Equation 3.2) for S = 30 m, V=40 miles/hour, deltaV=10 miles/hour with estimated parameters of table (5.2)

As observed in the comparison graph (Figure 3.3), for different conditions, there is no major difference between the calculated prospect functions except at the boundaries, but the total estimated utility (Figure 3.4) drops with a steeper slope for extreme condition with the increase in candidate acceleration. The moderate conditions also have a reduced total utility value compared to the normal condition. The curve converges to the normal condition curve as the acceleration gets closer to its maximum value. It can be then hypothesized that as the work zone conditions get more challenging, drivers estimate less total utility in obtaining higher accelerations. This observation includes that drivers anticipate higher losses inn more challenging conditions

After presenting the car-following formulation of the acceleration models that will be utilized in this thesis to understand the driver behavior at work zones, the following chapter will provide details on the data collection procedure adopted and the corresponding experimental set-up.

CHAPTER FOUR DATA ACQUISITION AND INITIAL ANALYSIS

In this chapter, the data collection methodology along with the experimental set-up are introduced. The resulting output measurements are then analyzed and the initial data analysis is offered.

4.1. Driving Simulator

The driving simulator located in the Center for Intelligence Systems Research (CISR) at The George Washington University Virginia science and technology campus (VSTC) is utilized in this study (see figure 4.1) to collect trajectory traffic data and to control the driving environment via providing visual and auditory stimuli. Sensors are located inside the simulator's vehicle to detect the driver's braking, steering, and throttle control signals. Driver feedback is provided with three LCD projectors, a 135-degree projection screen, steering wheel torque, and a sound system. Four networked computers drive the simulation. 3 computers generate images for the simulation, each one controlling one of the LCD projectors. The fourth computer generates realistic vehicle dynamics for the simulation, and it performs data acquisition.

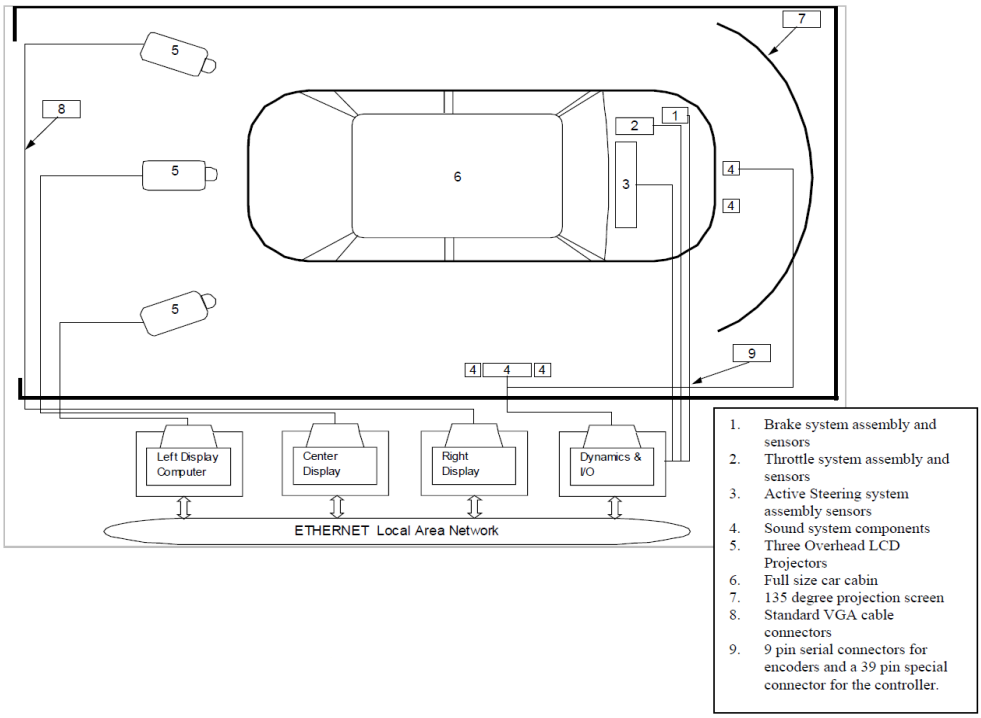

Figure 4.1 STISIM simulator structure (STISIM manual) located at CISR.

4.2. Data Collection Methodology

Using the driver simulator approach, the author has defined 8 different scenarios by changing the following variables which are considered as work zone characteristics in the STISIM software. The driver behavior characteristics such as acceleration and lane changing are observed through output information generated by each subject driver's performance. A wide array of data is produced by the simulator at each completion of the

simulation run. The system creates both a summary file of the events that occurred during the simulation run and snapshots of the vehicle and driver performance. Researchers can specify what data to save based on a list of possible variables. Details on designing the scenario and the corresponding participants are presented in the following subsections.

4.2.1. Experimental Setup

The used road-layout is a six lane urban highway with three lanes for each direction. Presence of two in-service lanes allows for observation of lane-changing while traveling the work zone area. Each lane is 12 feet wide. The right lane is then closed due to construction in the work zone area (figure 4.2). The car is initially located at the right lane. The work zone, the construction equipment, the traffic signs, the workers and vehicles appear as the driver starts moving in the simulated environment. Driver tends to change lanes as it approaches the work zone. The schematic bird-eye view of the work zone layout and snapshots of the simulated driving environment are presented in the following figures.

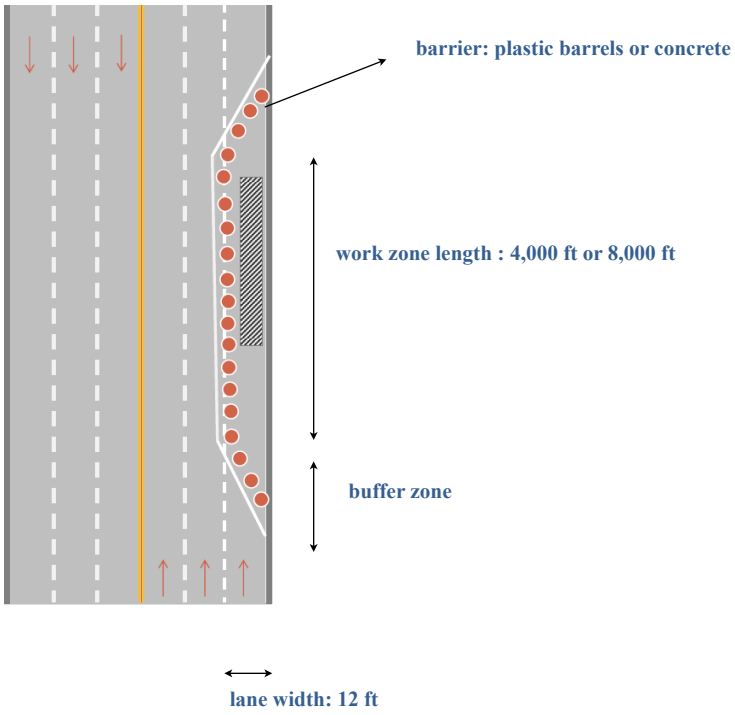

Figure 4.2 Work zone layout (The scales are not accurate.)

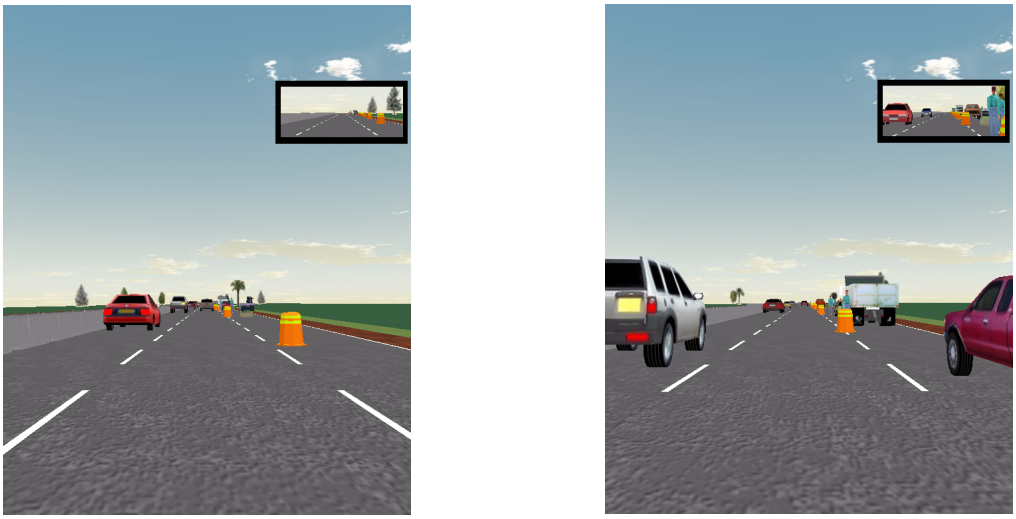

Figure 4.3 Snapshots of the driving experiment run.

The last variable that can be modified in the experiment is the work zone length. Such length is defined by the speed limit of the work zone (45 miles/hour from MUTDC) and the leader's acceleration pattern that should reflect realistic driving behavior, such behavior should include:

1. Acceleration from low speed (near complete stop) to high speed (near cruising speed) thresholds.

2. Deceleration from high speed to low speed threshold.

3. Short-term cruising at a constant speed (i.e., work zone speed limit).

The corresponding speed thresholds and acceleration/deceleration patterns are detailed in the following section (i.e., section 4.3) . Accordingly, 8 final scenarios with different work zone length, barrier type and activity levels are designed. These scenarios are shown in table 4.1.

Table 4.1 Scenario description by scenario ID number.

Scenario #	Work Zone Length	Barrier Type	Level of Activity
1	4,000 feet	Plastic Barrel	Low
2	4,000 feet	Jersey Barrier	Low
3	4,000 feet	Plastic Barrel	High
4	4,000 feet	Jersey Barrier	High
5	8,000 feet	Plastic Barrel	Low
6	8,000 feet	Jersey Barrier	Low
7	8,000 feet	Plastic Barrel	High
8	8,000 feet	Jersey Barrier	High

4.2.2. Level of Activity

The activity level is defined based on what Michelle L. Reyes and Sameer A. Khan (2010) used in their study and is based on real-life work zone set-ups. The first 500ft of the 9000ft activity area dose not contain any vehicles or workers In order to create a longitudinal buffer in the work zone, (see figure 4.2) the next 8000ft of the activity area is divided into two 4000ft activity zones. Work zone objects are placed in each zone depending on the level of activities.

High activity zones had the following number of objects in each 500ft segment:

- 1 dynamic work zone vehicle or 1 dynamic worker
- 4 static work zone vehicles
- 3 static workers in the closed lane of the work zone
- 2 static workers on the shoulder of the closed lane
- 2 passenger vehicles parked on the shoulder of the closed lane.

Low activity zones included the following number of objects in each 4000ft zone:

- 4 static work zone vehicles in the closed lane of the work zone
- 2 static work zone vehicles on the shoulder of the closed lane
- 4 static workers in the closed lane of the work zone
- 4 static workers on the shoulder of the closed lane
- 2 passenger vehicles parked on the shoulder of the closed lane

Once the work zone scenarios are defined, the surrounding traffic conditions must be designed in order to re-create a real-life driving environment.

4.3. Surrounding Traffic

In order to simulate a realistic traffic surrounding a given subject driver, linearized trajectory data patterns from the NGSIM trajectory repository (FHWA, Publication No. FHWA-HRT-07-030) are produced. The corresponding trajectory coordinates are collected through a portion of the corridor on southbound US 101 between the on-ramp at Ventura Boulevard and the off-ramp at Cahuenga Boulevard. Eight synchronized digital video cameras, mounted from the top of a 36-story building adjacent to the freeway, recorded vehicles passing through the study area. The corresponding area is illustrated below.

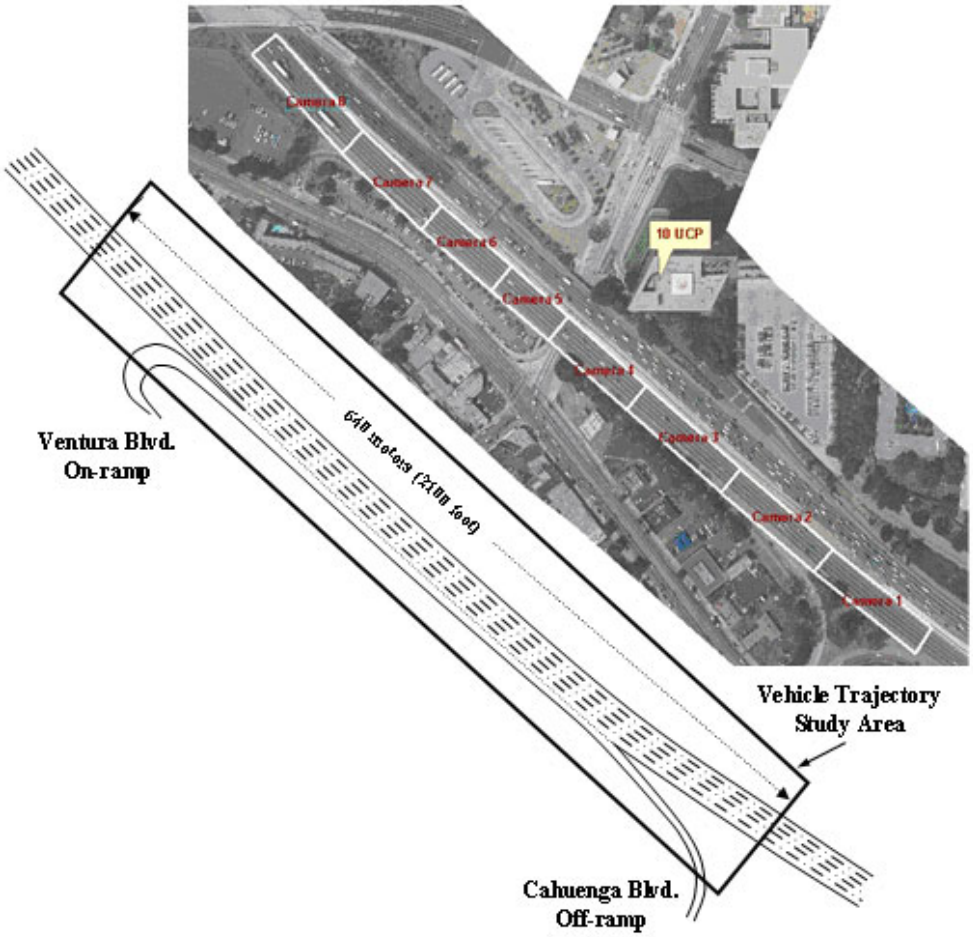

Figure 4.4 Extent of the US 101 study area. The schematic drawing on the bottom shows the number of lanes and location of the on-ramp at Ventura Boulevard and the off-ramp at Cahuenga Boulevard within the US 101 study area (Source :US highway 101 dataset fact sheet.)

There were several challenges tailoring the NGSIM data so that they can be incorporated in STISIM. NGSIM data for highway 101 provides the trajectory data on a **2100** feet highway stretch. However, given the specified speed limits in work zones, It

was found that the scenarios designed for this study should include work zones of **8000** feet and 4000 feet length plus the upstream and downstream distance in order to provide enough trajectory data for the calibration purposes. The upstream length is **5,000** feet before the work zone area starts and there is a **500** feet downstream buffer after the activity area ends; therefore, a maximum of $\mathbf{(8{,}000+5{,}000+500)/2{,}100 \simeq 7}$ vehicles with stop and go traffic patterns should be identified to simulate the traffic in the adjacent and travel lane surrounding the subject vehicle. The surrounding vehicles should not overlap while providing enough gaps to allow for lane-changing if needed. By going through the trajectory data again, finding vehicles with the mentioned traffic characteristics was proven to be difficult. The difficulty arises from the fact that even the slightest overlap of the vehicles would cause an unrealistic traffic stream in the simulation run (i.e., with collisions). This problem led to the idea of choosing one leading vehicle for each of the adjacent lanes and creating a longer trajectory data set for each leader by superposing the trajectory data of 7 different vehicles chosen from the NGISM data library. After studying the trajectory data of nearly 1500 vehicles collected between 8:20 am to 8:35 am, a group of vehicles including 7 passenger cars is selected. These seven vehicles travel a distance of 2100 feet in two adjacent lanes. The average headway between these vehicles is more than the accepted gap for lane changing based on the NGSIM data analysis report (US highway 101 dataset fact sheet). This claim allows the possibility for lane changing during the driving experiment. The selected vehicle numbers are 37, 39, 40,44,45,48 and 51. To be able to implement the data derived from NGSIM in the simulator, the surrounding vehicle's speeds need to be linearized (i.e., set of linear functions). STISIM

only allows for 21 points of slope change. Accordingly, one needs to find the best fit to the suggested NGSIM trajectory data using 22 linear functions. Three methods were tested for linearizing the data using MATLAB programming. The fits resulting from these methods are compared afterwards based on the coefficient of determination. The used methods are:

- Method I

This method chooses uniform time steps and fits one line to each segment using regression function.

- Method II

This method chooses uniform stretches on the scattered plot and fits a line to each stretch using regression function.

- Method III

This method initially fits a *n* degree polynomial curve to the data and then uses the local maximum and minimum points and inflection points for choosing the segments.

The method that provides the best linearized fit with the greatest coefficient of determination is chosen. Coefficient of determination, or R^2 is calculated as follows:

$$R^2 = 1 - SS_{resid} / SS_{total} \qquad \textbf{Equation 4.1}$$

$$SS_{resid} = \sum_i (y_i - f_i)^2 \qquad \textbf{Equation 4.2}$$

$$SS_{total} = \sum_i (y_i - \overline{y})^2 \qquad \textbf{Equation 4.3}$$

$$\overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \qquad \textbf{Equation 4.4}$$

n : number of trajectory data points from NGSIM data

y_i : vehicle speed from NGSIM data

f_i : estimated value of the vehicle speed from the fitted line

This method is method II. Even though the R^2 values did not converge to 1. The average coefficient of determinant is greater than the 0.5 showing a "somehow realistic" driving environment as the survey results indicates (appendix A). The corresponding fitting results are illustrated in figure 4.5. The speed profile is plotted along with the fitted lines.

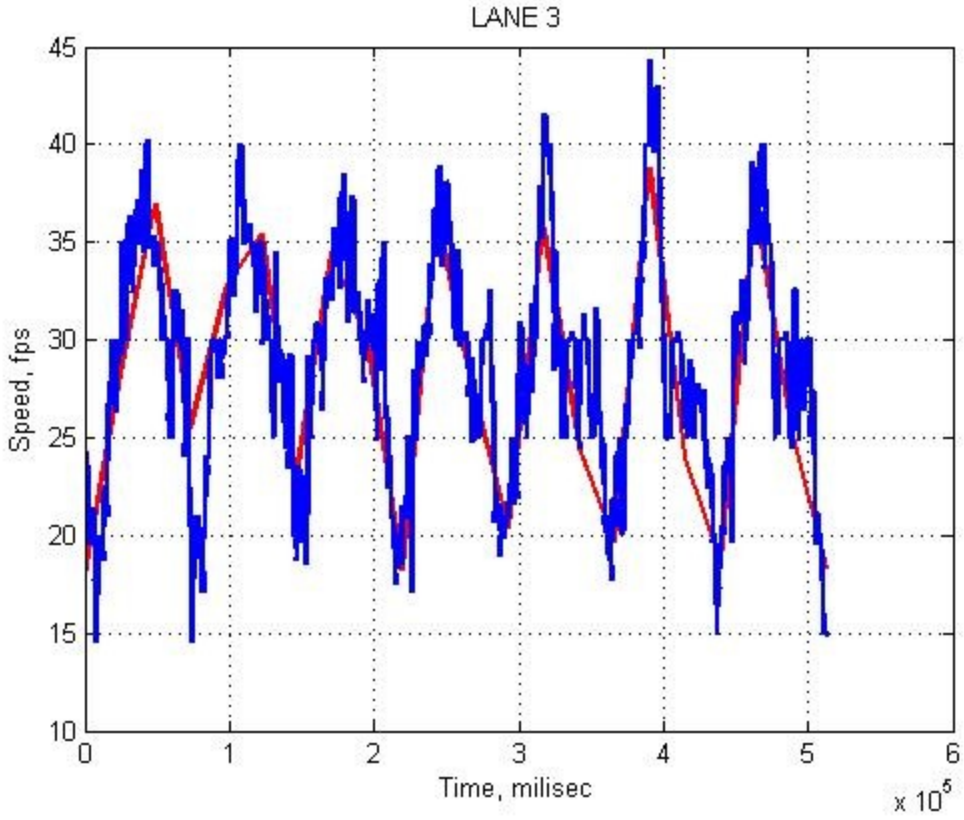

Figure 4.5 Linearization of superposed speed profiles of seven vehicles traveling on the lane 3 of 101 US highway.

After linearizing the trajectory data for each scenario, another challenge was faced due to the limitations of the car simulator. Defining a speed profile for any vehicle in the scene requires the use of "V event" (see table 4.2) and "action triggers" (with dynamic events, a trigger is needed that is used to trigger a particular action from the event [STISIM manual, 2004]); in this study the trigger for change in acceleration is the time elapsed since the beginning of the simulation run. This specification allows a trigger to occur based on how long the driver has been driving. Vehicles that are displayed using the V event have some intelligence built into them. If such vehicles are approaching

another vehicle from behind, or approaching a stop sign or traffic signal light, they will attempt to execute a pre-specified acceleration/deceleration maneuver. In the case of car-following behavior, a vehicle that is approaching another vehicle (including the subject's driver) from behind and in the same lane, will try to slow down in order to avoid rear-end collision with the lead vehicle. If a driver were to swerve in front of an approaching vehicle, the approaching vehicle will try to slow down, but it may not be enough to avoid a collision. Unfortunately, the vehicle "intelligence" only applies to speed. In other words, if the speed profiles are defined for all vehicles, no "action triggers" or "v-events" pre-specified responses may be built into the simulator (i.e., no intelligent vehicles may be incorporated in the simulator) . Once all of the pre-defined vehicle motions have been completed, the vehicle will revert back to an "intelligent" vehicle mode and will begin reacting to other vehicles and traffic control devices. Based on the above mentioned limitation and given the low average speed observed in the NGSIM data it is necessary that the subjective driver does not change lanes in a way that he/she overtakes the lead vehicle. The lead vehicle is on a predefined speed profile (figure 4.5) and will not be cognizant of the presence of another vehicle ahead. Such problem was solved by setting the lead vehicles speed to a high constant value before reaching the buffer zone and activating the NGSIM speed profile at the vicinity of the construction zone only. In the work zone, the confined driving space and the low speed thresholds prohibited the subject vehicles from making excessive overtaking maneuvers. The subject vehicle remained following the first lead vehicle in each lane. All the components of designed scenarios were put into graphics using SDL (scenario definition language). STISIM drive library

provides predefined events and 3D object models for building the scenarios. Events used in the work-zone scenarios are listed in the table below.

Table 4.2 Main events used in building the scenarios.

Event Abbreviation	Event	Event Description
A	Approaching Vehicle In Oposite Direction	Define oncoming traffic
V	Vehicle Moving In Drivers Direction	Define traffic in the direction of the driver
BLDG	Buildings	Display buildings at specific locations
BSAV	Begin Dynamic Data Block Save	Begin saving dynamic data that will be stored in the output data file
ROAD	Road	Display a specific roadway layout
SIGN	Traffic Sign	Display traffic signs at specific locations
JBAR	Jersey Barrier	Display jersey barriers at specific locations
PED	Pedestrian	Display pedestrians at specific locations
ES	End Simulation	Bring simulation to end
SOBJ	Static Object	Display a “static object” in the roadway display scene
TREE	Trees	Display trees at specific locations
CSET	Set Crash Parameters	Defines driver’s position after crash
BARL	Roadway Barrels	Display plastic barrels at specific locations

4.4. Participants

The key component in collecting the data is the participants contributing to this study. A total of 25 participants, with varying driving experience, were identified. A pre-experiment questionnaire was completed by each participant with questions about individual background and qualitative questions related to self driving perception. A post-experiment survey was filled by each driver. The average age of the participants is 24.1 years (std of 3.79 years), ranging from 20 to 32 year. Every participant had a valid U.S driving license and all the participants were in good general health condition. Table 4.3 shows the participants age, gender, the major accidents they have been involved with and the moving violation tickets they have received in the past three years. Out of 25 drivers, only 3 drivers has been in accidents and the average number of violation ticket for each driver is less than 1. Based on these information and the analysis of the answers provided, the driving sample is hypothesized to be homogeneous. Therefore, it could be expected that changes in drivers acceleration and lane-changing behavior is caused by external factors rather than inter-driving heterogeneity. For further details, the questionnaire and the survey used in this study are provided in appendices A and B respectively.

Table 4.3 Statistical information on participants

driver ID	age	gender	major accidents in last 3 yrs	moving violation tickets in last 3 yrs
1	20	m	0	0
2	22	f	0	0
3	20	f	0	2
4	20	m	0	0
5	22	m	0	0
6	20	m	0	0
7	29	m	0	2
8	21	m	1	0
9	24	f	0	0
10	32	f	0	0
11	20	m	1	0
12	29	m	0	1
13	22	m	0	1
14	32	m	0	0
15	22	m	0	0
16	24	m	0	0
17	24	m	0	0
18	26	m	0	2
19	25	f	0	0
20	22	f	0	0
21	28	m	1	1
22	26	m	0	0
23	21	m	0	0
24	24	m	0	0
25	29	m	0	1

4.3. Data

The data generated by STISIM software after each run is divided into 4 separate blocks: the event data block, the driver performance data block, driver mistakes data block and individual mistakes data block. In general, the system has the ability to record more than 40 parameters associated with driver behaviors. Since the study focuses on driver behavior form a traffic related perspective, most of the output data are taken from the driver performance block. The corresponding output variables used in this thesis are presented in the table 4.4.

Table 4.4 Output data description.

Column	Data Description
1	Elapsed time since the beginning of the run (seconds).
2	Driver's longitudinal acceleration (feet/second²).
3	Driver's lateral acceleration (feet/second²).
4	Driver's longitudinal velocity (feet/second).
5	Driver's lateral velocity (feet/second).
6	Total longitudinal distance that the driver has traveled since the beginning of the run (feet)
7	Drivers's lateral lane position with respect to the roadway dividing line, positive to the right(feet).
8	Running compilation of the crashed that the driver has been involved in.
9	Minimum time to collision (seconds) between the driver and all vehicles in the driver's direction.
10	Minimum range (ft) between the driver and all vehicles in the driver's direction.
11	Driver's response time (seconds) to any divided attention tasks.
12	Current speed limit (feet/second)
13-42	Saved data(longitudinal distance, lateral position and speed) for a specific numbered roadway object (the surrounding vehicles in this study).

4.4. Initial Analysis

In this subsection lane-changing and acceleration data are analyzed. Lane change occurrence is detected using a forward-backward algorithm in MATLAB in order to separate the vehicle deviation which is common in driving simulators from completed lane-change maneuvers. The number of lane changes in each scenario and the corresponding calculated lead and lag gaps are presented in the table below. The vehicle length used to calculate the gaps is 15 feet based on the vehicle's predefined characteristics in the STISIM setting. (STISIM manual)

Table 4.5 Observed lane-changing results and information

	Lane-Change #	Lead Gap(ft)	Lag Gap(ft)	Total Clear Gap(ft)	Level Of Activity	Barrier Type	Length(ft)
Scenario #2	1	25.1	124.57	164.67	low	Jersey	4000
Scenario #5	1	70.54	38.34	123.88	low	Drums	8000
	2	76.89	vehicle not in sight	NA	low	Drums	8000
	3	74.19	51.35	140.54	low	Drums	8000
	4	53.69	70.53	139.22	low	Drums	8000
	5	83.53	58.81	157.34	low	Drums	8000
Scenario #6	1	vehicle not in sight	31.75	NA	low	Jersey	8000
Scenario #7	1	84.73	43.03	142.76	high	Drums	8000

Scenario #8	1	221.03	vehicle not in sight	NA	high	Jersey	8000
	2	vehicle not in sight	36.31	NA	high	Jersey	8000
	3	67.78	144.25	227.03	high	Jersey	8000

The presented results indicate that the lane changing maneuvers were not frequently observed in our experiment. Only 11 lane changing maneuvers has been observed in 40 driving tests. Most of the lane changing takes place in the 8,000 feet scenarios. In fact, only 1 out of 11 observed lane changes happen in a short 4,000 feet long work zone area (scenario number 2). This could be an indicator of growing impatience while driving in a longer work zone with slow traffic. Another observation is that half of the lane changes in the 8000 feet long work zones happen in scenario number 5, which is a 8000 feet long work zone with low level of activity and drum barriers. Also, lane changing is more recurrent in low levels of activity. This can be interpreted as a more cautious driver behavior around high intensity work zone activities. Based on these observations, barrier types do not play a significant role in increasing or decreasing the frequency of lane changing. It should be noted that no additional numerical analysis related to the lane changing is performed at this stage due to the lack of related data (i.e., table 4.5). This conclusion may be due to the fact that there are no side mirrors incorporated in the driving simulator reducing the possibility of a safe lane changing maneuver when desired. Accordingly, no lane changing explicit modeling using microscopic traffic simulation is possible in this thesis.

4.4.1. Acceleration-Related Measurements

To discuss and compare the driver's acceleration behavior, the following measurements should be collected in different scenarios: average speed, average time headway and average space headway. Subject vehicle's speed was directly obtained from the output file at each 0.1 second and was averaged over the work zone length (figure 4.6). The average time headway and the average space headway was calculated using the trajectory data of the leading vehicle saved in the STISIM output file at each 0.1 second and was averaged over the work-zone area (figure 4.6 and figure 4.7).

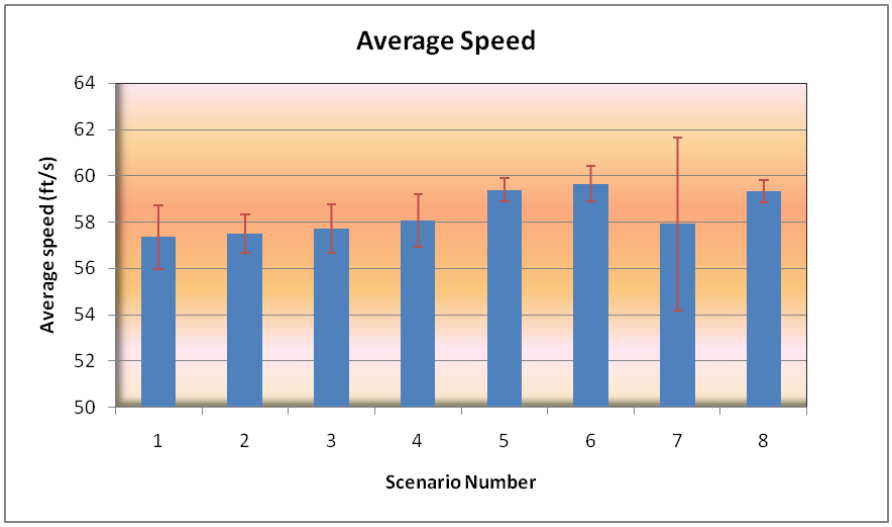

Figure 4.6 Average speed measurements for different scenarios.

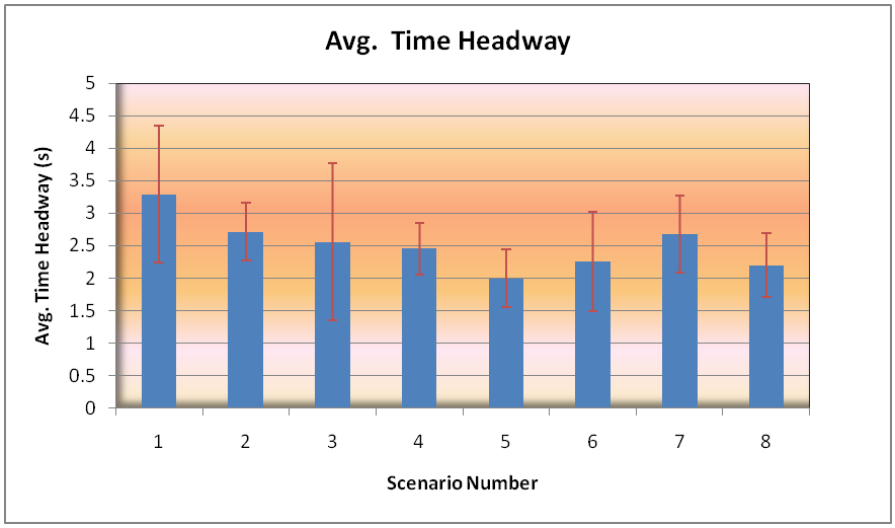

Figure 4.7 Average time headway measurements for different scenarios.

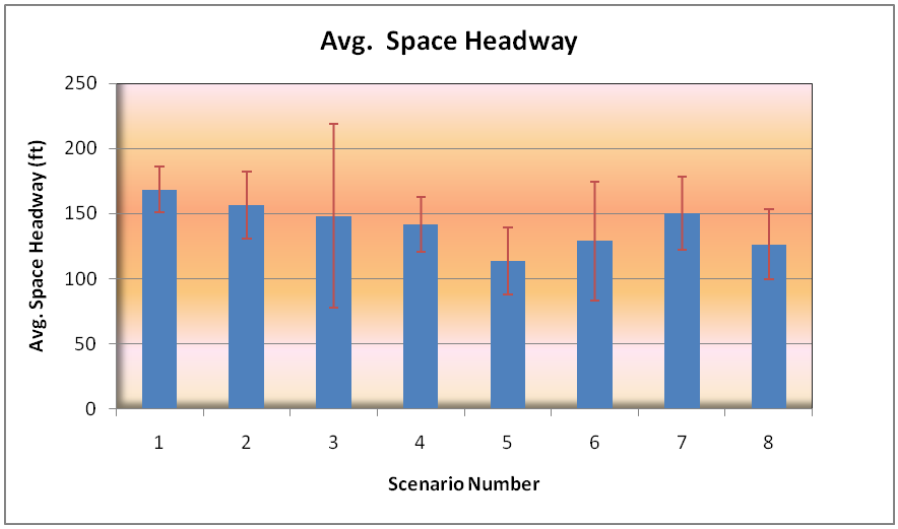

Figure 4.8 Average space headway measurements for different scenarios.

Keeping all other characteristics similar, the average speed (figure 4.6) is higher for the longer work zone scenarios (scenarios 5,6,7 and 8) compared to the short ones (scenarios 1,2,3 and 4). This finding could be another indicator of drivers' growing impatience over time. The graph also show that drivers attain a higher speed in presence of jersey barriers (scenarios 2,4,6 and 8) versus drums (scenarios 1,3,5 and 7) which was expected considering the better protection and separation provided by concrete jersey barriers. Looking at the graph for average speed we can also see that for both levels of activity drivers tend to travel in a lower speed in presence of drum barriers and the overall average speed is higher for low level activities (scenarios 1,2,5 and 6). As for the average space headway (figure 4.8) , It is observed that drivers tend to keep a shorter headway in longer work zones. The only inconsistency happens in the results for a high activity work zone with drum barriers (Scenario 7). In this case, the longer work zones are associated with larger space headway values by a small margin. The difference is so small that could be considered negligible. This could mean that the effect of combined high activity and drum type barriers, which is the most intense scenario in terms of activity intensity and work zone separation, overshadows the length of the work zone and drivers keep almost the same safe distance from the leading vehicle regardless of how long they drive in the work zone area. Another interesting observation is that comparison between bars for barrier types show that average space headway for work zones with jersey barrier is shorter than work zones with drum barriers. There is no notable pattern considering only the level of activity in work zone which can be an indicator of

prevalence of barrier type and length effect. In terms of average time headway, the two significant observations based on these graphs are completely consistent with previous results which is keeping a shorter time headway in long scenarios with jersey barriers.

4.5. ANOVA Tests

Even though the graphical and visual analysis using figures 4.6 through 4.8 allowed reaching some basic conclusions, a more statistically rigorous testing/analysis is needed. For such purpose, the Analysis of variance (ANOVA) test is utilized in this section. The results from ANOVA tests are summarized in the following tables. Although the test results does not show significance of the work zone variable's contribution to the change in variance within groups, this could be the result of speed limit and surrounding traffic restrictions on subject drivers. In other words the speed and headways are changing in limited ranges and the standard deviations are small to begin with. The highlighted cells in the following tables show which factors contribute with more statistical significance to changes in general acceleration measures within groups.

Table 4.6 ANOVA test results for average speed.

4000 feet length								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Activity	0.33	1.00	0.33	0.27	4.49	8.53	16.12	3.05
Barrier	1.07	1.00	1.07	0.86	4.49	8.53	16.12	3.05
Activity*Barrier	0.06	1.00	0.06	0.05	4.49	8.53	16.12	3.05
Error	19.88	16.00	1.24					
Total	21.35	19.00						
8000 feet length								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Activity	3.48	1.00	3.48	0.94	4.49	8.53	16.12	3.05
Barrier	3.99	1.00	3.99	1.07	4.49	8.53	16.12	3.05
Activity*Barrier	1.62	1.00	1.62	0.44	4.49	8.53	16.12	3.05
Error	59.55	16.00	3.72					
Total	68.65	19.00						
Jersey Barriers								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
length	0.08	1.00	0.08	0.11	4.49	8.53	16.12	3.05
Activity	14.40	1.00	14.40	20.66	4.49	8.53	16.12	3.05
Activity*Length	1.00	1.00	1.00	1.43	4.49	8.53	16.12	3.05
Error	11.15	16.00	0.70					
Total	26.63	19.00						
Drum Barriers								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
length	1.53	1.00	1.53	0.36	4.49	8.53	16.12	3.05
Activity	6.27	1.00	6.27	1.47	4.49	8.53	16.12	3.05
Activity*Length	4.14	1.00	4.14	0.97	4.49	8.53	16.12	3.05
Error	68.28	16.00	4.27					
Total	80.22	19.00						
high level of activity								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Length	3.91	1.00	3.91	0.95	4.49	8.53	16.12	3.05
Barrier	2.67	1.00	2.67	0.65	4.49	8.53	16.12	3.05
Length*Barrier	1.36	1.00	1.36	0.33	4.49	8.53	16.12	3.05
Error	65.74	16.00	4.11					
Total	73.67	19.00						
low level of activity								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Length	0.22	1.00	0.22	0.25	4.49	8.53	16.12	3.05
Barrier	19.60	1.00	19.60	22.90	4.49	8.53	16.12	3.05
Length*Barrier	0.01	1.00	0.01	0.02	4.49	8.53	16.12	3.05
Error	13.69	16.00	0.86					
Total	35.70	19.00						

It is observed that in scenarios with jersey barriers and low level of activities, activity level and barrier type contribute more significantly to changes in average speed respectively.

Table 4.7 ANOVA test results for average time headway.

4000 feet length								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Activity	0.56	1.00	0.56	1.16	4.49	8.53	16.12	3.05
Barrier	1.16	1.00	1.16	2.41	4.49	8.53	16.12	3.05
Activity$_x$Barrier	0.27	1.00	0.27	0.55	4.49	8.53	16.12	3.05
Error	7.71	16.00	0.48					
Total	8.98	19.00						
8000 feet length								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Activity	0.06	1.00	0.06	0.17	4.49	8.53	16.12	3.05
Barrier	0.48	1.00	0.48	1.40	4.49	8.53	16.12	3.05
Activity$_x$Barrier	0.66	1.00	0.66	1.93	4.49	8.53	16.12	3.05
Error	5.50	16.00	0.34					
Total	6.70	19.00						
Jersey Barriers								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
length	0.12	1.00	0.12	0.41	4.49	8.53	16.12	3.05
Activity	0.64	1.00	0.64	2.16	4.49	8.53	16.12	3.05
Activity$_x$Length	0.05	1.00	0.05	0.18	4.49	8.53	16.12	3.05
Error	4.73	16.00	0.30					
Total	5.54	19.00						
Drum Barriers								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
length	0.00	1.00	0.00	0.01	4.49	8.53	16.12	3.05
Activity	1.66	1.00	1.66	3.13	4.49	8.53	16.12	3.05
Activity$_x$Length	2.35	1.00	2.35	4.43	4.49	8.53	16.12	3.05
Error	8.48	16.00	0.53					
Total	12.41	19.00						
high level of activity								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Length	0.40	1.00	0.40	1.30	4.49	8.53	16.12	3.05
Barrier	0.02	1.00	0.02	0.08	4.49	8.53	16.12	3.05
Length$_x$Barrier	0.16	1.00	0.16	0.53	4.49	8.53	16.12	3.05
Error	4.87	16.00	0.30					
Total	5.83	19.00						
low level of activity								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Length	0.13	1.00	0.13	0.25	4.49	8.53	16.12	3.05
Barrier	3.84	1.00	3.84	7.38	4.49	8.53	16.12	3.05
Length$_x$Barrier	0.87	1.00	0.87	1.67	4.49	8.53	16.12	3.05
Error	8.33	16.00	0.52					
Total	13.18	19.00						

It is observed that in scenarios with drum barriers, activity level and combination of activity level and length and for scenario with low level of activities, barrier type contribute more significantly to changes in average time headway.

Table 4.8 ANOVA test results for average space headway

4000 feet length								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Activity	425.30	1.00	425.30	0.27	4.49	8.53	16.12	3.05
Barrier	1549.47	1.00	1549.47	0.97	4.49	8.53	16.12	3.05
Activity$_x$Barrier	33.26	1.00	33.26	0.02	4.49	8.53	16.12	3.05
Error	25619.07	16.00	1601.19					
Total	27627.10	19.00						
8000 feet length								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Activity	93.74	1.00	93.74	0.09	4.49	8.53	16.12	3.05
Barrier	1426.74	1.00	1426.74	1.35	4.49	8.53	16.12	3.05
Activity$_x$Barrier	1876.63	1.00	1876.63	1.77	4.49	8.53	16.12	3.05
Error	16968.53	16.00	1060.53					
Total	20365.64	19.00						
Jersey Barriers								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
length	383.07	1.00	383.07	0.39	4.49	8.53	16.12	3.05
Activity	2289.23	1.00	2289.23	2.34	4.49	8.53	16.12	3.05
Activity$_x$Length	196.68	1.00	196.68	0.20	4.49	8.53	16.12	3.05
Error	15678.72	16.00	979.92					
Total	18547.71	19.00						
Drum Barriers								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
length	323.32	1.00	323.32	0.19	4.49	8.53	16.12	3.05
Activity	3455.86	1.00	3455.86	2.05	4.49	8.53	16.12	3.05
Activity$_x$Length	3983.03	1.00	3983.03	2.37	4.49	8.53	16.12	3.05
Error	26908.87	16.00	1681.80					
Total	34671.08	19.00						
high level of activity								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Length	1151.19	1.00	1151.19	0.66	4.49	8.53	16.12	3.05
Barrier	217.52	1.00	217.52	0.13	4.49	8.53	16.12	3.05
Length$_x$Barrier	363.78	1.00	363.78	0.21	4.49	8.53	16.12	3.05
Error	27700.53	16.00	1731.28					
Total	29433.02	19.00						
low level of activity								
Source	Sum of squares	df	Mean Square	F-Value	p=0.05	p=0.01	p=0.001	P=0.1
Length	13.13	1.00	13.13	0.01	4.49	8.53	16.12	3.05
Barrier	8442.67	1.00	8442.67	9.07	4.49	8.53	16.12	3.05
Length$_x$Barrier	900.83	1.00	900.83	0.97	4.49	8.53	16.12	3.05
Error	14887.06	16.00	930.44					
Total	24243.69	19.00						

In terms of average space headway (ASH), barrier type is the most statistically significant contributor to changes of ASH in low level activity scenarios.

CHAPTER 5: MODEL CALIBRATION AND NUMERICAL ANALYSIS

The acceleration model presented in chapter 3 is calibrated using the data obtained from the driving simulator (see chapter 4). Accordingly, an initial data mining and procession phase is required to isolate the trajectory information. Such information includes the time-step, the acceleration rate, the velocity, the longitudinal coordination, the lateral coordination and the time headway at every 0.1 second. The information is collected along the work zone area in each of the conducted 40 experiments. In this chapter, the adopted calibration algorithm is presented first. The corresponding results are then analyzed. For a more thorough discussion, the MANOVA test is utilized to make sure that the change in the parameter values is due to the external driving conditions (i.e., work zone characteristics) and not due to the inter-driver differences (i.e. , heterogeneity). The MANOVA testing details are discussed in section 5.3. The final statistical analysis is presented in section 5.4.

5.1. The Genetic Algorithm Calibration

Due to the structure of the suggested acceleration model, a genetic algorithm is used to estimate the parameters of extended prospect theory based acceleration functions. The Genetic algorithm (GA) is a search algorithm that utilizes techniques inspired by evolution process in nature like mutation, crossover, selection and inheritance. It searches

globally for the "optimal" solution, that is the optimal simultaneous combination of investigated parameters of the extended PT function.

For every set of empirical data (i.e., experiment) obtained from the driving simulator, the calibration code based on the GA should produce a solution. To such end, implementing a typical genetic algorithm needs:

1. a genetic representation of the solution domain,

2. a fitness function to evaluate the solution domain,

The parameters to be estimated in the GA solution are re-mentioned below:

- Gene γ : It defines the shape of the asymptotics of the generalized PT utility; one may mention that the more extreme the driver's reaction to external factors, the higher the estimated value of γ is.

- Gene W_m : It represents the weight of the prospect theory's relative losses in speed with respect to gains associated with a change in velocity.

- Gene W_c : It reflects an individual's subjective sensitivity to the losses that are caused by a potential rear-end collision.

- Gene $\tau_{\max}$: It reflects the maximum anticipation time horizon

- Gene α : It reflects the subject driver's uncertainty about the leading vehicle's speed, the more uncertain and defensive the driver is, the higher the values of α are.

- Gene β: It is the logit uncertainty parameter which reflects the sensitivity to the PT utility.

- Gene τ_{corr}: It represents the correlation time of intra-driver variability. The smaller the τ_{corr} is, the greater the fluctuations in acceleration choices are.

- Gene *RT*: It defines the driver's reaction time.

Each set of the above mentioned genes create a chromosome and each chromosome is a member of a population.

5.2. Fitness Function

Once the chromosome used in the GA implementation is defined, a fitness function needs to be introduced. This fitness function allows for the evaluation of the solution domain by comparing the observed trajectory and the simulated trajectory. In this study the driver's observed car-following behavior is compared to the simulated car-following model and the difference between them is minimized by choosing the "optimal" parameters for the simulated model. This procedure is called model calibration. To minimize the difference, a correct choice of the error measurement (i.e. , fitness function) is necessary. In this study, due to errors in recording the space gaps in STISIM data at times of lane-changing or post-crash runs, space gap based error is not adopted and the calibration procedure is performed based on velocity measurements. The objective error function adopted by (Hamdar et al., 2008) is a mixed velocity error defined as:

$$F_{mix}\left[v^{sim}\right]=\sqrt{\frac{1}{\left|v^{data}\right|}\left\langle\frac{(v^{sim}-v^{data})^2}{\left|v^{data}\right|}\right\rangle} \qquad \textbf{(Equation 5.1)}$$

Where $v^{sim}(t)$ and $v^{data}(t)$ are the empirical and simulated velocity time series and $\langle\cdot\rangle$ refers to the temporal average of a time series of duration ΔT. In other words, for a time series "*z*" ;

$$\langle z\rangle=\frac{1}{\Delta T}\int_0^{\Delta T} z(t)\,dt \qquad \textbf{(Equation 5.2)}$$

The above mixed error is adopted after considering two different error measures. The first measure is the relative error which is defined as:

$$F_{rel}\left[v^{sim}\right]=\sqrt{\left\langle\left(\frac{(v^{sim}-v^{data})}{v^{data}}\right)^2\right\rangle} \qquad \textbf{(Equation 5.3)}$$

This measure is weighted by the inverse of the observed velocity v^{data} which makes the function more sensitive to small velocities than to large velocities.

The second measure is the absolute error measure which is defined as:

$$F_{abs}\left[v^{sim}\right]=\sqrt{\frac{\left\langle (v^{sim}-v^{data})^2\right\rangle}{\left\langle v^{data}\right\rangle^2}} \qquad \textbf{(Equation 5.4)}$$

In this measure the denominator is averaged over the whole trajectory interval; therefore the absolute error is less sensitive to small deviations in the observed data if compared to the relative error. The absolute error is also more sensitive to large differences in the numerator (Hamdar et al., 2008). To avoid the overestimation of errors at high and low velocities equation 5.1 will be used in the GA "optimization" process as detailed below.

First, the initial population of possible solutions (10 parent chromosomes) are created using gene values in the proximity of those provided and tested in Hamdar et al. (2008). Parent chromosomes produce 90 offsprings in each iteration. From the total of (90+10) chromosomes, 10 best fitted chromosomes are selected to parent the next generation. The best fitted chromosomes are the ones that generate the smallest fitness function values (equation 5.1). Each 2 offspring chromosomes are generated from two parent chromosomes (see figure 5.1). This cycle defines the calibration iteration.The crossover point is randomly selected.

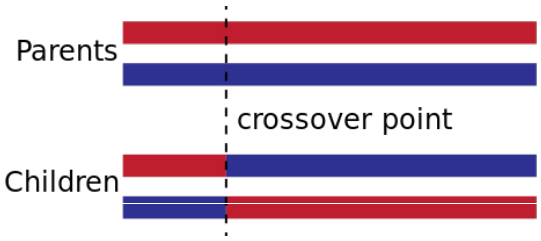

Figure 5.1 Crossover method

Following the nature rules of mutation, to maintain genetic diversity from one generation of chromosomes to the next, the GA allows for mutation of offspring by changing the genes randomly following a given probability (i.e., 10%). Only the chromosome with the best fitness score does not go through mutation. This mutation process allows escaping "local optimum" regions and thus improves the calibration exercise's performance. The calibration iterations continue until convergence. Convergence is reached when the error reaches the threshold of 15% or when no improvement of more than 0.01 is observed in error for 300 consecutive iterations.

5.2. Initial results

The following table shows the GA solution for each set of trajectory data grouped by scenario ID numbers as described in chapter 4.

Table 5.1 Estimated parameter values for each set of driving experiment outputs.

scenario	#	Gamma	Wm	Wc	Tmax	Alpha	Beta	Tcorr	Reaction Time	MixedError Velocity
1	1	0.2	2	100000	4	0.08	10	28	1	0.090852
	2	0.2	2	100000	4	0.08	10	28	1	0.089077
	3	0.2	2	100000	4.1	0.18	8	20	0	0.107896
	4	0.2	6	60000	6	0.11	3	23	27	0.08494
	5	0	0.6	131000	3.4	0.18	10.6	14	7	0.344691
2	1	0.2	2	100000	4	0.08	10	28	1	0.123968
	2	0.2	2	100000	4	0.08	6	15	18	0.137843
	3	0.2	6	60000	6	0.11	3	23	27	0.109769
	4	0.2	2	100000	4	0.08	10	28	1	0.059017
	5	0.2	2	100000	4	0.08	10	28	1	0.098367
3	1	0.2	2	100,000	4	0.08	10	28	1	0.059538
	2	0.2	2	100000	4	0.18	9.8	28	1	0.096638
	3	0.2	2	100000	4	0.18	10	28	1	0.124983
	4	0.2	6	60000	6	0.11	3	23	27	0.081404
	5	0.2	2	100000	4	0.41	10	28	1	0.077514

	1	0.4	7	130000	3	0.07	8	14	1	0.136802
	2	0.2	2	100000	4	0.18	8	14	26	0.080446
	3	0.2	2	100000	4	0.08	10	28	1	0.084014
	4	0.2	6	60000	6	0.11	3.3	28	1	0.111644
4	5	0.2	2	100000	4	0.08	10	28	1	0.040681
	1	0.2	2	100000	7.3	0.07	8	29	1	0.143872
	2	0.2	2	100000	4	0.08	10	28	1	0.061586
	3	0.2	2	100000	4	0.08	10	28	1	0.088378
	4	0.2	2	100000	4	0.08	10	28	1	0.052921
5	5	0.2	2	100000	4	0.08	10	28	1	0.027142
	1	0	0.9	149000	4.7	0.09	10.9	14	1	0.360463
	2	0.2	2	100000	4	0.18	8	14	26	0.113155
	3	0.2	6	60000	6	0.11	3	23	27	0.136154
	4	0	3	140000	4	0.29	10	11	1	0.143341
6	5	0.2	2	100000	4	0.08	10	28	1	0.062094
	1	0.2	2	60000	7.1	0.18	8	20	0	0.115621
	2	0.2	2	100000	4	0.08	10	28	1	0.07575
	3	0.4	5.5	130000	6	0.07	8.5	24	1	0.117151

	4	0.2	2	100000	4	0.08	10	28	1	0.065645
7	5	0.2	2	100000	4	0.08	10	28	1	0.067783
	1	0.2	2	100,000	4	0.08	10	28	1	0.07233
	2	0.2	2	100000	4	0.08	10	28	1	0.115003
	3	0.2	2	100000	4	0.08	10	28	1	0.07036
	4	0.2	2	100000	4	0.08	10	28	1	0.060541
8	5	0.2	2	100000	4	0.18	8	14	26	0.146316

The scenarios are also grouped into extremely challenging (noted as extreme), moderately challenging (noted as moderate) and normally challenging (noted as normal) conditions to "statistically" analyze the changes in GA generated parameters. For this purpose, the following work zone classification scheme is hypothesized:

• Extremely challenging condition : high level of activity in an 8,000 feet work zone with plastic barrels captured in scenario #7.

• Normally challenging Condition: low level of activity in a 4,000 feet work zone with concrete barriers captured in scenario #2.

• Moderately challenging condition: one or two of the following conditions occur. High level of activity, plastic barrels and 8,000 feet (i.e., scenario #1,3,4,5,6 and 8).

The mean values for the 9 estimated parameters for each type of condition (i.e., different challenge levels) are represented in the following table and graphs.

Table 5.2 Mean values for estimated parameters in different conditions.

condition	Gamma	Wm	Wc	Tmax	Alpha	Beta	Tcorr	Reaction Time	MixedError Velocity
extreme	0.24	2.7	98000	5.02	0.098	9.3	25.6	0.8	0.08839
moderate	0.19	2.65	99667	4.35	0.125	8.72	23.9	6.27	0.10882
noraml	0.2	2.8	92000	4.4	0.086	7.8	24.4	9.6	0.10579

A better visual illustration for comparing the values represented in table 5.2 is offered in appendix C.

In another attempt to better understand the effect of the external factors on the changes in the estimated parameters, the scenarios are divided into two separate groups based on the external work zone variables. The mean values of the estimated parameters in each group are represented in the following table and graphs.

Table 5.3 Mean values for estimated parameters in different length.

length(ft)	Gamma	Wm	Wc	Tmax	Alpha	Beta	Tcorr	Reaction Time	MixedError Velocity
4,000	0.2	2.98	95050	4.32	0.127	8.13	24.1	7.52	0.10700
8,000	0.19	2.68	98415	4.44	0.117	8.66	24.2	6.03	0.10591

Table 5.4 Mean values for estimated parameters in different barrier types.

barrier	Gamma	Wm	Wc	Tmax	Alpha	Beta	Tcorr	Reaction Time	MixedError Velocity
cone	0.2	2.5	97050	4.6	0.123	8.94	25.8	3.8	0.09867
concrete	0.19	2.67	98464	4.44	0.117	8.68	24.2	5.95	0.10571

Table 5.5 Mean values for estimated parameters in different activity levels.

activity	Gamma	Wm	Wc	Tmax	Alpha	Beta	Tcorr	Reaction Time	MixedError Velocity
low	0.17	2.52	100000	4.47	0.11	8.52	23.3	7.25	0.12178
high	0.19	2.67	98536	4.44	0.116	8.67	24.1	6.03	0.10627

The values represented in tables 5.3 to 5.5 are illustrated and compared in figures 5.2 to 5.9. For better illustration purposes, the parameters with similar value ranges are put together in the corresponding graphs. The calculated PT function and total utility function values for the parameters represented in tables 5.3 to 5.5 are plotted in appendix D.

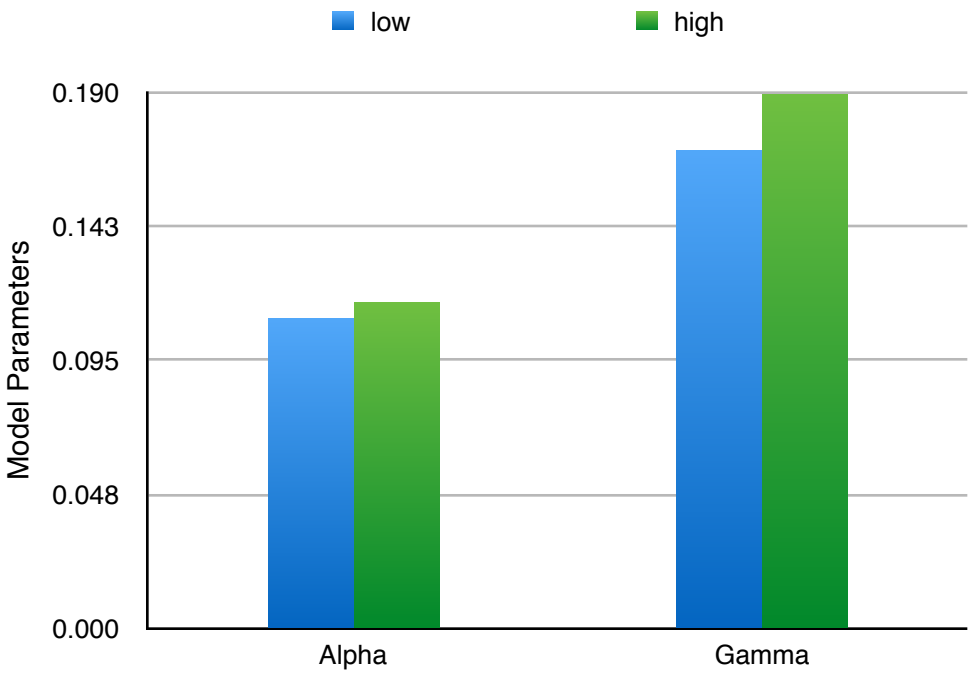

Figure 5.2 Comparison of estimated parameters α and γ for level of activity

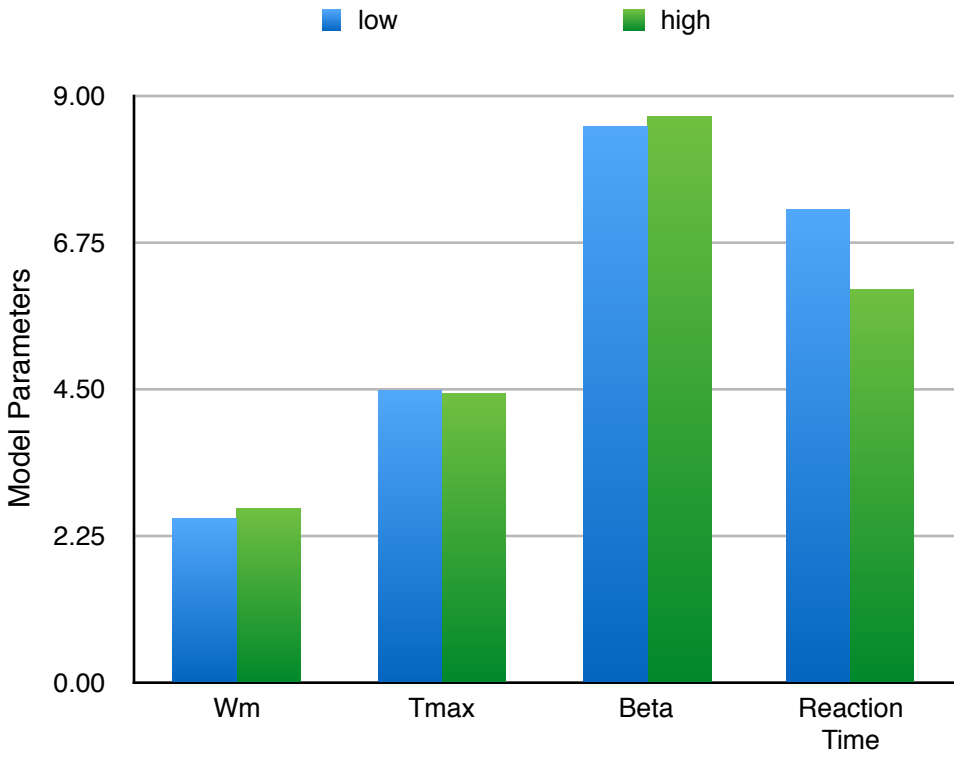

Figure 5.3 Comparison of estimated parameters W_m, $\tau_{\max}$, β and Reaction Time for level of activity

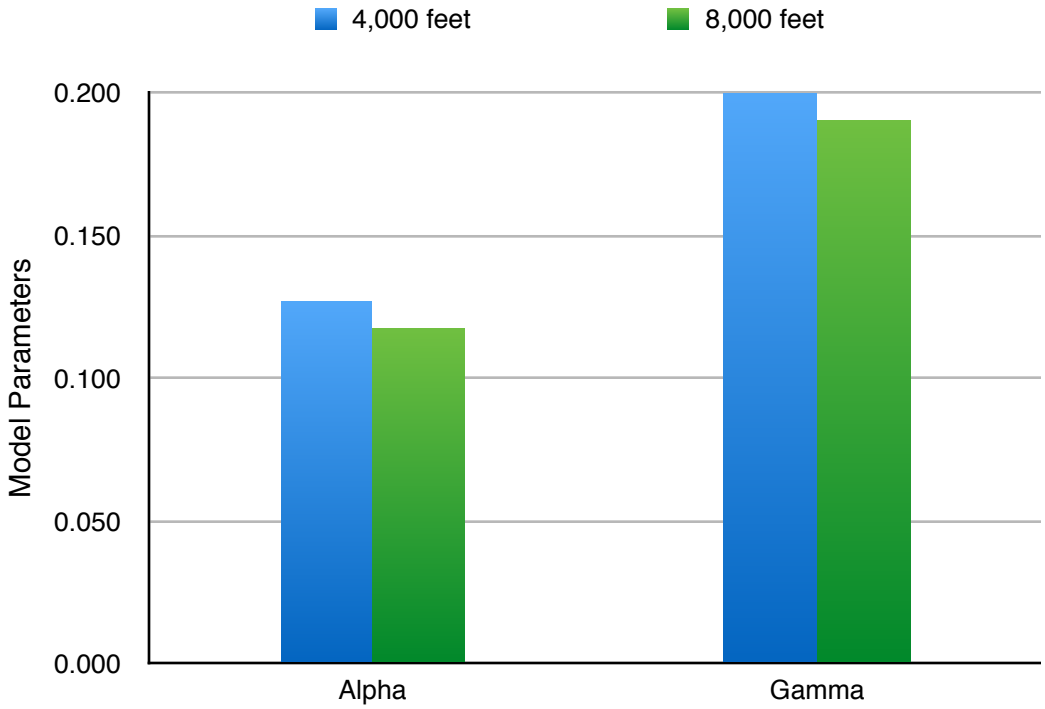

Figure 5.4 Comparison of estimated parameters α and γ for length

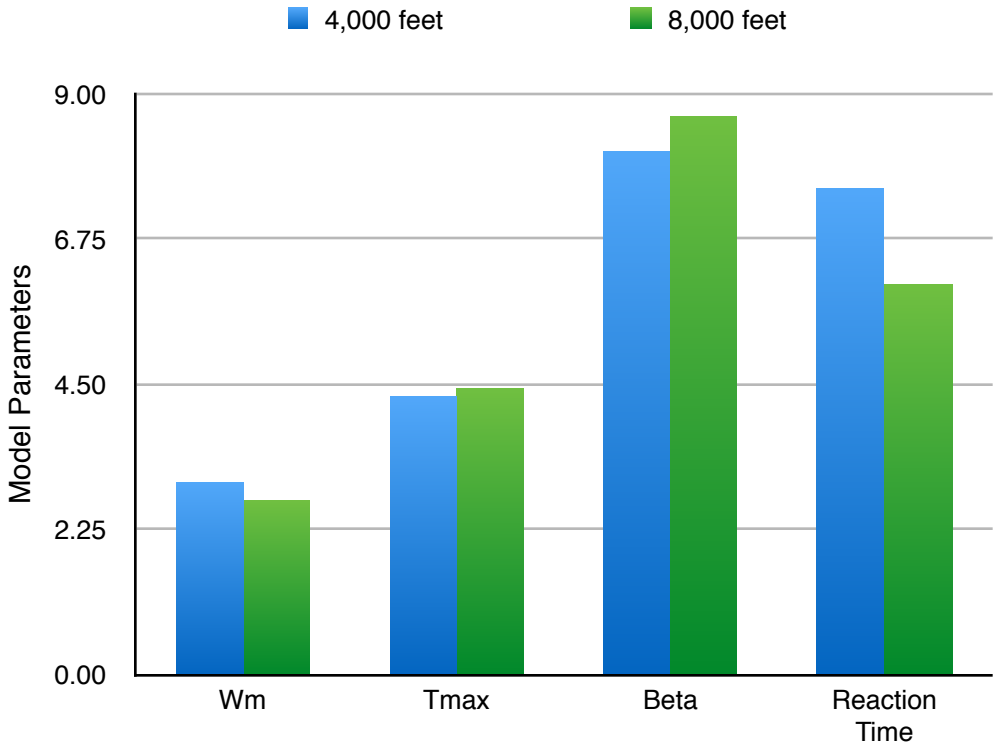

Figure 5.5 Comparison of estimated parameters W_m, $\tau_{\max}$, β and Reaction Time for length.

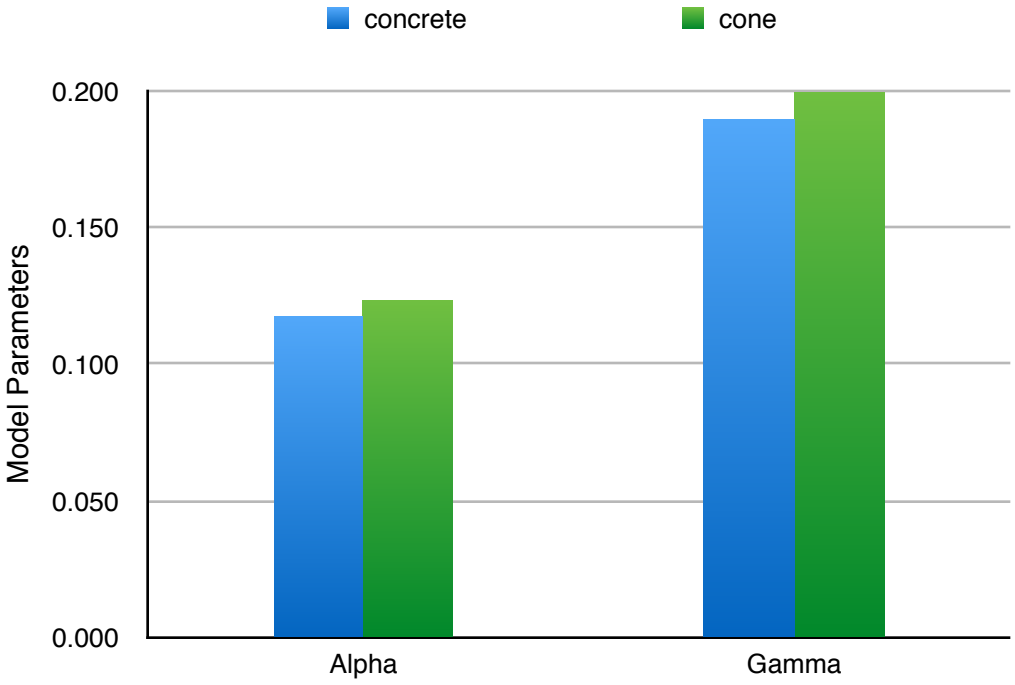

Figure 5.6 Comparison of estimated parameters α and γ for barrier type.

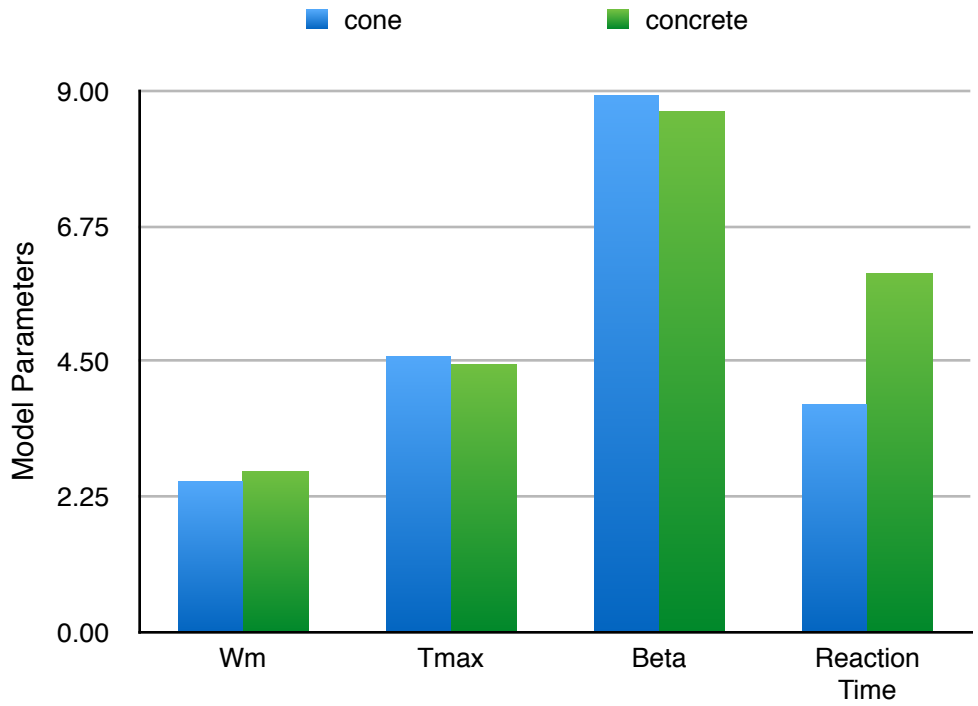

Figure 5.7 Comparison of estimated parameters W_m, $\tau_{\max}$, β and Reaction Time for barrier type.

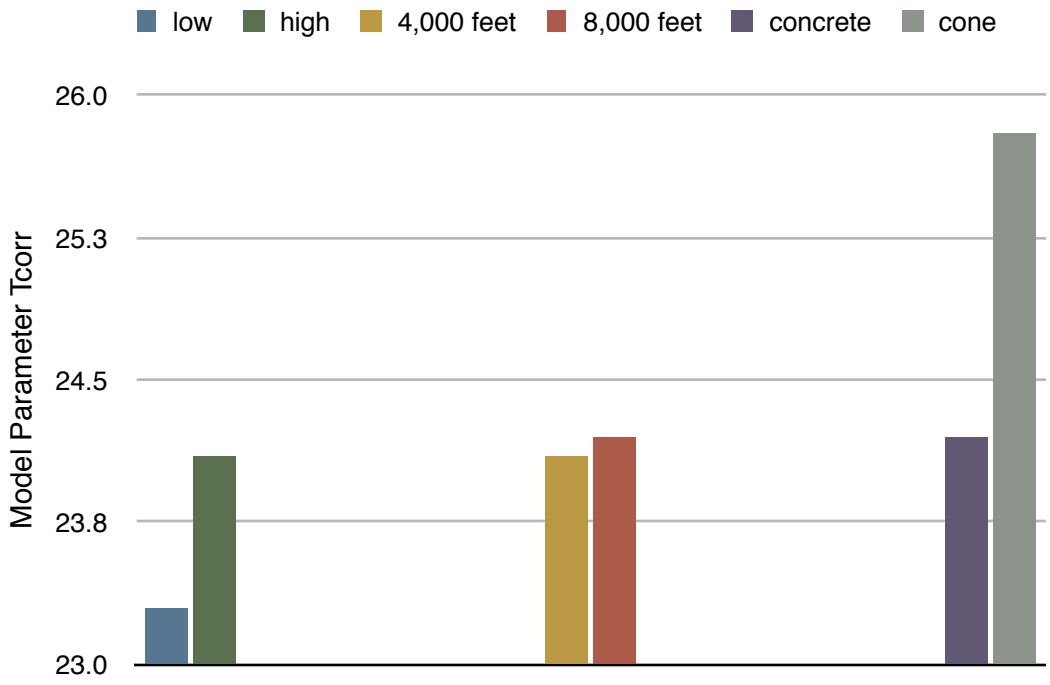

Figure 5.8 Comparison of estimated parameters W_c.

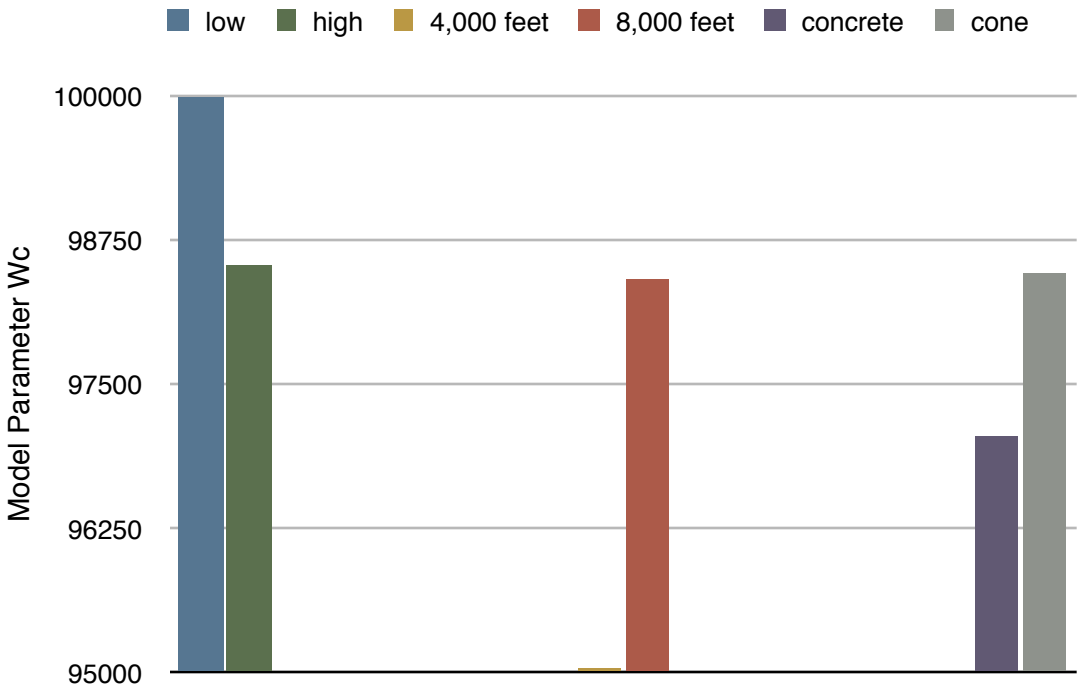

Figure 5.9 Comparison of estimated parameters τ_{corr}.

Based on the presented tables and graphs the following major findings may be mentioned.

First, γ has a higher value for extremely challenging conditions (table 5.2), when plastic barrels are utilized (figure 5.6) and when work zones have high activity levels (figure 5.2). This finding may be an indicator of drivers more extreme reaction to external factors during challenging driving conditions. Moreover, the γ value is less for longer work zone areas (figure 5.4) which can be an indicator of an inertia effect in the driver's reaction since drivers get used to external work zone related changes over time.

The second finding is related to evaluating losses and gains in velocity. W_m is higher when concrete barriers (figure 5.7) and high level of activities (figure 5.3) are observed. In other words, during high activity levels drivers may need to be more risk averse, thus putting more weight on the losses in velocity compared to the weight put on the gain in velocity. As for the concrete barriers, driver may need to have higher deceleration tendencies due to the possible side-collision with concrete barriers given the possible resulting damages to the vehicle. This maybe contrasted to the limited losses when dealing with collision with "soft" barriers.

Finally, one may notice the higher values of parameter α when plastic barrels are used (figure 5.6), during high activity level (figure 5.2) and for short-length work zones (i.e., 4000ft, figure 5.4). In other words drivers may be more defensive in environments with these characteristics. An increase in α is an indicator of uncertainty producing

lower speeds and thus more defensive driving. Despite the reasonable connections found between the estimated parameters and the exogenous variables as illustrated in the preceding graphs and tables, there is still no proof that the observed differences are the results of changing the exogenous independent variables. To answer the question of wether the differences in the estimated parameters (dependent variables) are due to changes in external factors (independent variables) with statistical significance, the following sections are purposed to discuss the MANOVA test and the corresponding results.

5.3. Multivariate Analysis of Variance (MANOVA) Test

The term analysis of variance indicates analytical techniques that are dealing with the evaluation of group differences. These groups may be defined in any number of ways that represent different levels of a particular independent variable. In case of having more than two groups, a method is needed to evaluate differences amongst those groups simultaneously, since pairing these groups can increase the number of tests exponentially. In this study, MANOVA helps answering these question:

1. Do changes in the independent variables (type of barrier, length of work zone and level of activity in the work zone) have significant effects on the mean values of dependent variables (estimated PT parameters)?

2. What are the interactions among the dependent variables and among the independent variables?

To proceed answering these questions through one-way MANOVA testing, 9 assumptions must be made. The first four assumptions has to be checked by the researcher (through experimental set-up), while the last five assumptions can be checked by using the SPSS software (through statistical modeling and analysis):

- Assumption #1: The dependent variables should be measured at the interval or the ratio level (i.e., they are continuous). In this study, the estimated model parameters are the dependent variables which are all ratio variables.

- Assumption #2: The independent variables should consist of two or more categorical, independent groups. In this study, the independent variables are barrier type, work zone length and activity level. The combination of independent variable values/types produce another classification scheme: extreme, normal and moderate condition. The corresponding two types of classifications are categorical.

- Assumption #3: The observations should be independent, which means that there is no relationship between the observations in each group or between the groups. In this thesis, the experimental set-up has been designed in a way that the number of participants and the driving scenarios ensure independence of observation.

- Assumption #4: There should be an adequate sample size to conduct the testing. For MANOVA, there should be more cases in each group than the number of dependent variables to be analyzed. The categorization which groups results based on barrier type, length and level of activity passes this assumption. Each group has 20 cases which is almost twice the number of dependent variables. The second

categorization which groups results based on the challenge level in each scenario does not pass this assumption completely, therefore MANOVA test has not been performed for the second classification scheme. The final 5 assumptions are related to the statistical modeling and the corresponding data produced:

- Assumption #5: There are no univariate or multivariate outliers.
- Assumption #6: There is multivariate normality.
- Assumption #7: There is a proportionality relationship between each pair of dependent variables for each group of independent variables.
- Assumption #8: There is a homogeneity of variance-covariance matrices.
- Assumption #9: There is no multicollinearity.

The MANOVA based results are explained for each of the independent variables (work zone length , barrier type and level of activity) through two tests: the Levene's test and the multivariate test

First, the Levene's test of equality of error variances, tests the assumption that the variances of each variable are equal across the groups. If the Levene's test fails, this means that the assumption has been violated – and data should be viewed with caution – or the data could be transformed so as to equalize the variances. The reported significance should be greater than 0.05 in order to pass the Levene's test. The results obtained corresponding to the work zone length, barrier type and activity level are presented in tables 5.6, 5.7 and 5.8 respectively. The columns labeled "df" give the degrees of freedom

associated with the MANOVA test. The columns labeled “F” show the F-value of MANOVA test.

Table 5.6 Levene’s Test of Equality for independent variable length.

	F	df1	df2	Sig.
Gamma	.301	1	38	.586
Wc	1.188	1	38	.283
Wm	.359	1	38	.553
Tmax	.327	1	38	.571
Alpha	.613	1	38	.439
Beta	.056	1	38	.814
Tcorr	.722	1	38	.401
Reaction.time	.390	1	38	.536
MixedError.Gap	.	1	38	.
MixedError.Velocity	.178	1	38	.676

Table 5.7 Levene’s Test of Equality for independent variable barrier.

	F	df1	df2	Sig.
Gamma	.791	1	38	.379
Wm	.328	1	38	.570
Wc	1.541	1	38	.222
Tmax	3.221	1	38	.081
Alpha	.051	1	38	.822
Beta	.214	1	38	.646
Tcorr	.267	1	38	.608
Reaction.time	.212	1	38	.648
MixedError.Gap	.	1	38	.
MixedError.Velocity	.279	1	38	.600

Table 5.8 Levene's Test of Equality for independent variable level of activity.

	F	df1	df2	Sig.
Gamma	.005	1	38	.944
Wm	.301	1	38	.587
Wc	1.290	1	38	.263
Tmax	.821	1	38	.371
Alpha	.000	1	38	1.000
Beta	.000	1	38	.994
Tcorr	.002	1	38	.963
Reaction.time	.001	1	38	.982
MixedError.Gap	.	1	38	.
MixedError.Velocity	.001	1	38	.973

For all the reported *p*-values which are labeled by sig. in the above tables, it is observed that the *p*-value is greater than 0.05, therefore the null hypothesis and the equality of variances passes and the author can continue with the MANOVA test.

Comparing the *p*-values for an estimated parameter in different groups, one can tell what type of external change can affect that particular model parameter more than others.

Parameter γ changes more significantly (*p*-value = 0.994) by the change in activity level. In other words activity level in the work zone can significantly affect the intensity of the driver's reaction to the external factors. Moreover, the length of work zone is a more important contributor to the changes in γ if compared to the barrier type.

In addition, the level of activity and the barrier type impact the driver's estimation of the relative losses to gains (W_m) significantly especially if compared to the work zones

length. On the other hand, reaction time (*RT*) is most sensitive to the changes in level of activity (*p*-value=0.982).

The differences in significance (*p*-value) for parameter W_c are not as large as other parameters. This finally may indicate that drivers' sensitivity to the losses that are caused by a potential accident does not change significantly by changing one independent variable or another. This may be related to the method through which W_c is defined and the corresponding scale value (order of 10^5). One may tackle this issue by replacing W_c by $\ln(W_c)$ on the future formulation.

Finally, the significance of the impact of the level of activity on parameter α for level of activity (*p*-value=1) is greater than the ones related to the barrier type. This result may indicate that changes in level of activity impacts the drivers uncertainty about the leader's relative speed and this leads to more conservative driving in high activity work zones. Following the same logic, τ_{corr} is also more significantly affected by the changes in the work zone level of activity (*p*-value=0.963) if compared to changes in the other independent variables.

Another type of testing may be of use in this study. The multivariate analysis testing results are presented in the following tables.

Table 5.9 Multivariate test results for independent variable length.

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	1.000	153344766[b]	9.000	30.000	.000
	Wilks' Lambda	.000	153344767[b]	9.000	30.000	.000
	Hotelling's Trace	46003429.98	153344767[b]	9.000	30.000	.000
	Roy's Largest Root	46003429.98	153344767[b]	9.000	30.000	.000
length	Pillai's Trace	.175	.706[b]	9.000	30.000	.698
	Wilks' Lambda	.825	.706[b]	9.000	30.000	.698
	Hotelling's Trace	.212	.706[b]	9.000	30.000	.698
	Roy's Largest Root	.212	.706[b]	9.000	30.000	.698

Table 5.10 Multivariate test results for independent variable barrier

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	1.000	157256929[b]	9.000	30.000	.000
	Wilks' Lambda	.000	157256929[b]	9.000	30.000	.000
	Hotelling's Trace	47177078.58	157256929[b]	9.000	30.000	.000
	Roy's Largest Root	47177078.58	157256929[b]	9.000	30.000	.000
barrier	Pillai's Trace	.788	12.375[b]	9.000	30.000	.000
	Wilks' Lambda	.212	12.375[b]	9.000	30.000	.000
	Hotelling's Trace	3.713	12.375[b]	9.000	30.000	.000
	Roy's Largest Root	3.713	12.375[b]	9.000	30.000	.000

Table 5.11 Multivariate test results for independent variable level of activity.

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	1.000	159583767[b]	9.000	30.000	.000
	Wilks' Lambda	.000	159583767[b]	9.000	30.000	.000
	Hotelling's Trace	47875130.17	159583767[b]	9.000	30.000	.000
	Roy's Largest Root	47875130.17	159583767[b]	9.000	30.000	.000
activity	Pillai's Trace	.205	.861[b]	9.000	30.000	.569
	Wilks' Lambda	.795	.861[b]	9.000	30.000	.569
	Hotelling's Trace	.258	.861[b]	9.000	30.000	.569
	Roy's Largest Root	.258	.861[b]	9.000	30.000	.569

It could be observed that for level of activity and work zone length, the statistical significance of the impact of the exogenous variables is greater than 0.05 threshold value for all the tests. This finding indicates that behavior differs more significantly with changes in the level of activity and the work zone length if compared to the changes in the barrier type. It should be noted that this does not mean that all the parameters are effected more significantly by changes in the level of activity. As it was discussed in the previous section, different dependent parameters are sensitive to different types of external variables.

CHAPTER 6: CONCLUSIONS

In this chapter the major findings of this study are summarized and future research recommendations are offered.

6.1. Summary of Results

Due to the maintenance requirements of the aging roadway infrastructures, work zone areas are encountered more frequently by existing drivers. Such work zones have significant impact on the safety and the mobility of traffic specially during peak hour conditions. The objective of this study is to analyze driving behavioral changes with respect to different work zone features. A PT-based acceleration model is utilized for this purpose. The corresponding formulation framework is presented in chapter 3. After proper experimental set-up, an initial analysis of the output data looked into the average speed and headway measurements (indicators of longitudinal driver behavior) as a function of different exogenous factors (i.e., work zone layout characteristics). Work zones characterized by low-level activity, long stretches of activity area and concrete barriers were associated with higher average speeds and shorter space headways. To understand the significance of the external variables' impact on such speed and headway variations, ANOVA test was performed. In order to quantify the impact of the external factors on the drivers perception and execution processes, the PT model parameters were calibrated in different scenarios for each driver. A genetic algorithm was utilized for such purpose. The corresponding calibration was followed by a series of multivariate analysis

of variance (MANOVA) tests in chapter 5 to assess the sensitivity of each PT model parameter to each external factor. Level of activity in the work zone has the most significant impact on parameter γ (p-value = 0.994): This finding indicates that the intensity of a driver's reaction (i.e., acceleration rate) to changes in work zone's level of activity is the highest. The results also show that the length of a work zone (p-value = 0.586) is a more important contributor to the changes in γ if compared to the barrier type (p-value = 0.379).

As for the risk taking attitude, the drivers perception of the relative losses in speed with respect to relative gains (i.e., parameter W_m) is impacted more significantly by the level of activity (p-value=0.587) and the barrier type (p-value=0.570) than by the work zone length. In terms of alertness, a driver's reaction time (RT) is most sensitive to the changes in the level of activity (p-value=0.982). On the other hand, uncertainty about the leading vehicle's future speed (i.e., parameter α) is significantly affected by the level of activity (p-value=1) and the barrier type (p-value=0.822). The fluctuations in acceleration, represented by the parameter τ_{corr} (correlation time), is also impacted the most by the changes in the level of activity (p-value=0.963).

6.2. Future Research Recommendations

Based on the survey results collected in this study, most of the participants agree that the simulated environment in the STISIM simulator is “somewhat realistic” and does not fully reflect the real life work zone condition. Upgraded versions of STISIM include an open module plug-in software which enables the user to interface to STISIM Drive with programming languages like C++ to create custom applications or expand the simulator's functionality resulting in a more realistic driving environment. Moreover, in order to increase the reliability of the obtained trajectory data and make sure that they capture the driver behavior in real life, it is recommended that similar studies use different data collecting methods such as using an instrumental vehicle in real work zones. This method may also allow looking into driver lateral maneuvering in work zones since understanding driver’s lane-changing behavior in work zones is essential to capture traffic mobility and safety. It should be noted that the limited side view in the used simulator environment caused fewer lane-changing maneuvers: gaps were rejected even when the critical gap in the adjacent lane was acceptable. Finally, different utility functions may be examined and calibrated in order to find the best performance function fit for modeling the driver’s acceleration behavior in work zones. Such functions may be used to conduct a more extensive sensitivity analysis to understand the impact of individuals driving behavior on the collective traffic patterns in work zone conditions.

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APPENDIX A

Driving Behavior Survey

Subject ID [Filled out by Research Assistant]: ……..…… Survey Date and Time [Filled out by Research Assistant]: ……

Please answer each of the following items as honestly as possible. Please read each item carefully and then circle or check the box corresponding to the answer you choose on the form. If none of the choices seem to be your ideal answer, then select the answer that comes closest. THERE ARE NO RIGHT OR WRONG ANSWERS. Select your answers quickly and do not spend too much time analyzing your answers. If you change an answer, erase the first one well._The expected completion time of this survey is 10 minutes.

I. **Please indicate your level of agreement with the following statements:**

Section 1:	Strongly Disagree	Disagree	Neither Agree Nor Disagree	Agree	Strongly Agree
1. I am a confident driver.	€	€	€	€	€
1. I believe I have enough experience and training to deal with risky situations on the road safely.	€	€	€	€	€
1. I get a real thrill out of driving fast.	€	€	€	€	€
1. I enjoy the sensation of accelerating rapidly.	€	€	€	€	€

1.	I consider myself to be a risk-taker.	€	€	€	€
1.	I like to raise my adrenaline levels while driving.	€	€	€	€
1.	I feel that most traffic "laws" could be considered as suggestions.	€	€	€	€
1.	Driving brings out the worst in people.	€	€	€	€
1.	I feel it is my right to get where I need to go as quickly as possible.	€	€	€	€
1.	I consider the actions of other drivers to be inappropriate or "stupid".	€	€	€	€
1.	I feel it is my right to strike back in some way, if I feel another driver has been aggressive toward me.	€	€	€	€
1.	I feel that passive drivers (who are slow to react) should learn how to drive or stay home.	€	€	€	€
1.	I tend to disregard traffic laws when I see others disregarding them.	€	€	€	€

II. Please indicate how often you engage in the following driving behaviors or experience the following situations:

Section 2:	Never	Rarely	Sometimes	Often	Always
1. I exceed the speed limit without realizing it.	€	€	€	€	€
1. I intentionally disregard the speed limit.	€	€	€	€	€
1. I intentionally cross a red light.	€	€	€	€	€
1. I drive even when I am angry or upset.	€	€	€	€	€
1. I lose my temper while driving.	€	€	€	€	€
1. I flash my headlights when I am annoyed by another driver.	€	€	€	€	€
1. I honk the horn when I am annoyed by another driver.	€	€	€	€	€
1. I make rude or inappropriate gestures towards drivers who annoy me.	€	€	€	€	€
1. I verbally insult drivers who annoy me.	€	€	€	€	€
1. I deliberately use my car to block drivers who tailgate me (follow me closely).	€	€	€	€	€
1. I would tailgate a driver who annoys me.	€	€	€	€	€
1. I race other drivers at traffic lights to get ahead once lights turn green.	€	€	€	€	€
1. I will illegally pass a car/truck that is going too slowly.	€	€	€	€	€
1. When I get stuck in a traffic jam I get very irritated.	€	€	€	€	€
1. I will weave (move from lane to lane) to avoid slower traffic.	€	€	€	€	€
1. When someone cuts me off (changes lane in front of me abruptly), I feel I should punish him/her.	€	€	€	€	€
1. I get impatient and/or upset when I fall behind schedule when I am driving.	€	€	€	€	€
1. Passengers in my car/truck tell me to calm down.	€	€	€	€	€

1. I get irritated when a car/truck in front of me slows down for no reason.	€	€	€	€
1. I will drive in the shoulder lane or median (extreme right or left) to get around a traffic jam.	€	€	€	€

III. Demographics:

1. How many hours do you study/work (academic or non-academic, for pay) per week? _____

2. How many hours did you drive today?

_____

3. How many of these were in heavy traffic?

_____

4. How many hours do you drive on an average weekday?

_____

5. How many days a week do you drive on average?

_____

6. Do you own the vehicle you drive?

_____

7. Please indicate the make, model, and the year of manufacture of this vehicle:

Make (e.g. Honda, Mercedes, etc.): _____ Model (e.g. Accord, 3-Series, etc.): _____ Year of manufacture: _____

8. How many major accidents in the past 3 years have you been involved in as a driver? _____

9. How many moving violation tickets (speeding tickets, tickets for crossing red lights, etc., but not including tickets obtained for not wearing the seatbelt) have you been given in the past 3 years as a driver?

_____

IV. Finally, we'd like to ask you a few questions below about the driving experiments you just did using the simulator.

1. Overall, to what extent did driving in the simulator feel like real world driving?

Not at all close ☐ Somewhat close ☐ Very close ☐

2. How realistic did the driving speed in the simulator feel to you?

Very unrealistic ☐ Somewhat realistic ☐ Very realistic ☐

3. To what extent did you feel dizzy while driving the simulator?

Not at all ☐ A little ☐ Very much ☐

4. Do you believe that dizziness or other factors affected your driving behavior in the simulator to differ from your actual driving behavior on the roads?

Not at all ☐ A little ☐ Very much ☐

V. If you have any comments about this survey or the drive in the driving simulator, please write them below:

_____

_____

_____

_____

_____

_____

_____

_____

APPENDIX B

Driving Behavior Study Using a Driving Simulator

Screening Interview

Subject ID [Filled out by Research Assistant]: .....

Interview Date [Filled out by Research Assistant]: .....

We will ask you now a few questions to make sure you are eligible to participate in this study.

1. **Do you have a driver's license?**

   ☒ Yes
   ☒ No

   [If "No", interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 2.]

2. **Do you currently drive?**

   ☒ Yes
   ☒ No

[If "No", interviewer proceeds to Question 2b; otherwise, interviewer proceeds to Question 3.]

2b. How long has it been since you stopped driving?

……

[If answer to Question 2b is 3 years or more, interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 3.]

3. [Health related issues]

a. Are you on medications?

☒ Yes

☒ No

b. Have you ever complained of dizziness?

☒ Yes

☒ No

c. Do you have any ear or eye problem?

☒ Yes

☒ No

d. Do you have any motion sickness?

☒ Yes

☒ No

e. **Have you had any recent sleep deprivations?**

☒ Yes

☒ No

f. **Do you have any active medical problems such as heart problems, epilepsy, etc.?**

☒ Yes

☒ No

g. **Do you have any active psychiatric problems such panic disorder, etc.?**

☒ Yes

☒ No

h. **Do you have Alzheimer's disease?**

☒ Yes

☒ No

[If subject answers "Yes" to any of the above questions, interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 4.]

4. **[Interviewer notes respondent's gender.]**

☒ Male

☒ Female

[If subject is female, interviewer proceeds to Question 5; otherwise, interviewer proceeds to Question 6].

5. Are you pregnant?

☒ Yes

☒ No

[If subject is pregnant, interviewer thanks the subject and tells her that she is not eligible to participate in the study]

6. What is your age?

……

[If age is less than 18, interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study]

7. a. What is your occupational status at GWU?

☒ Student

☒ Employee

b. If student, what are your faculty and major of study?

Faculty

……
……

Major of study

……
……

c. If student, what is your current educational status?

- ☒ Freshman
- ☒ Sophomore (first year)
- ☒ Junior (second year)
- ☒ Senior (third year or above)
- ☒ Graduate (Masters or Ph.D. student)
- ☒ Medicine

d. If employee, what is your job type?

- ☒ Academic
- ☒ Management
- ☒ Non-academic, non-management

APPENDIX C

Comparison graphs for model parameters between scenarios with different challenge levels are represented here.

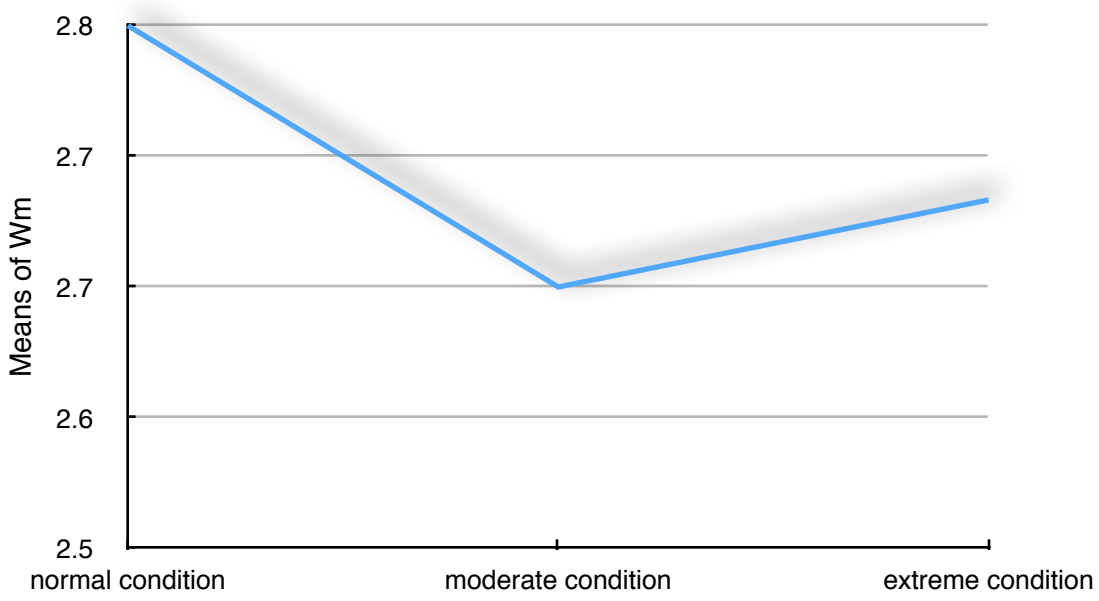

Figure C.1 Comparison of the mean values for estimated parameter W_m.

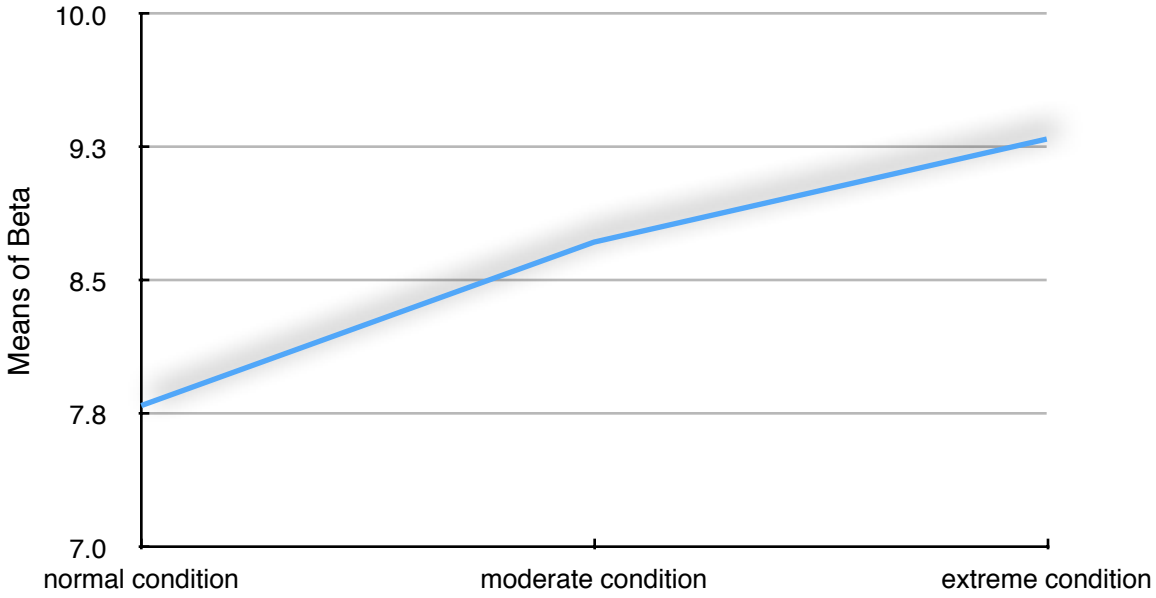

Figure C.2 Comparison of the mean values for estimated parameter β.

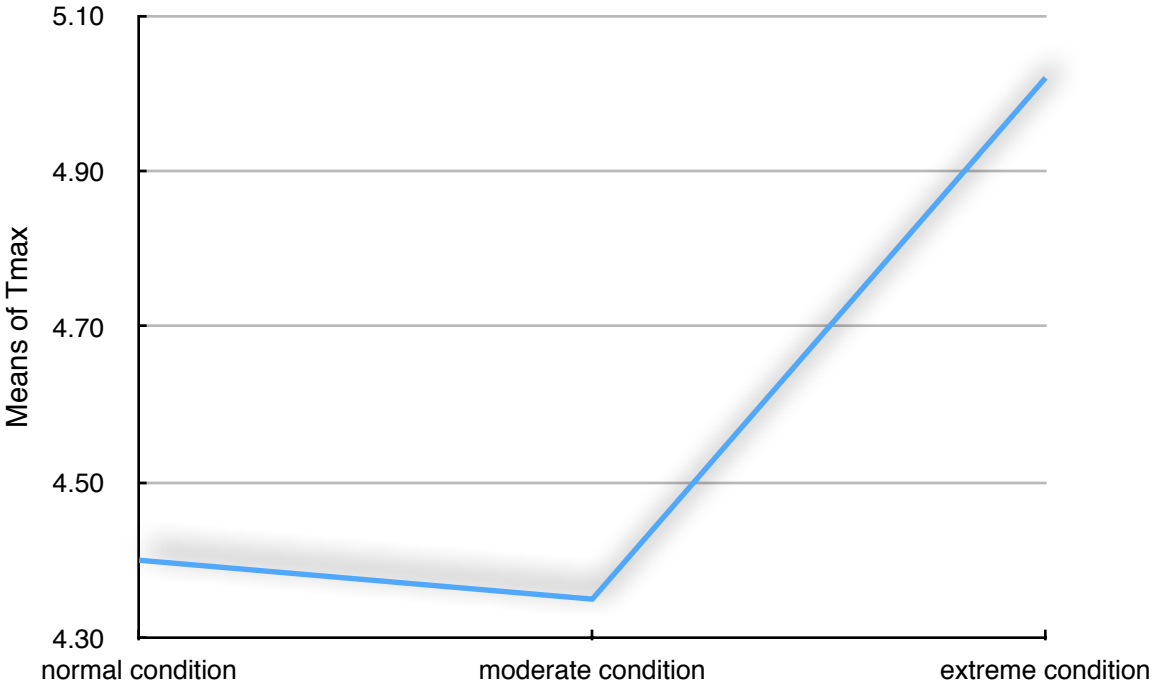

Figure C.3 Comparison of the mean values for estimated parameter τ_{max}.

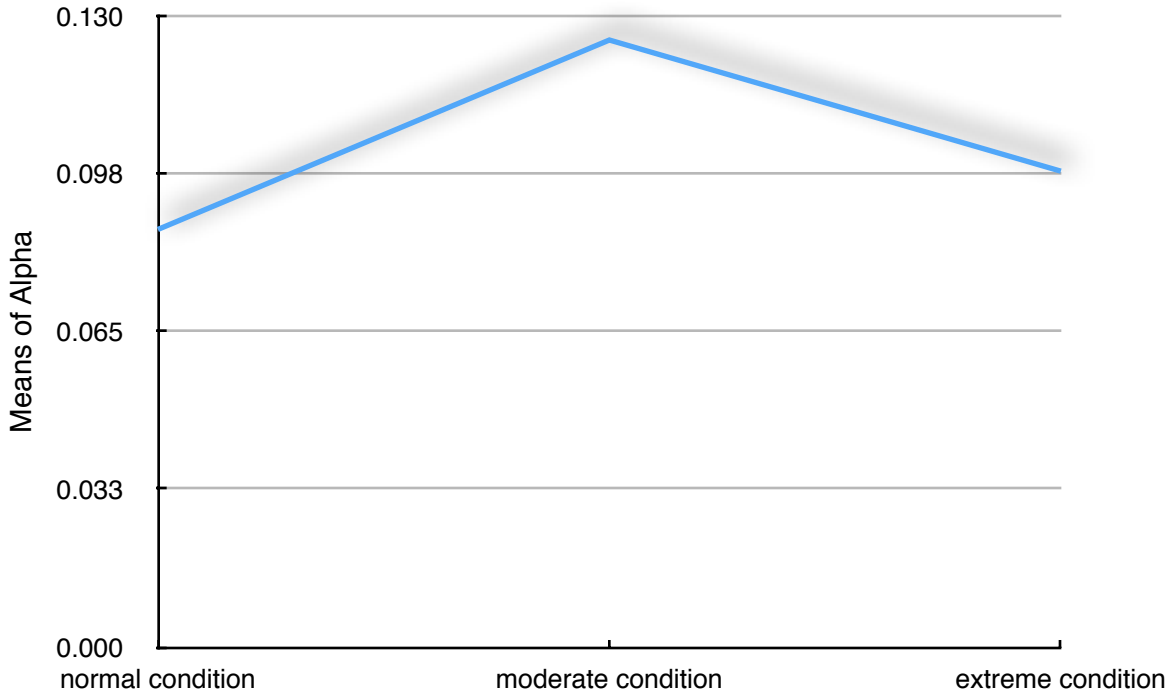

Figure C.4 Comparison of the mean values for estimated parameter α.

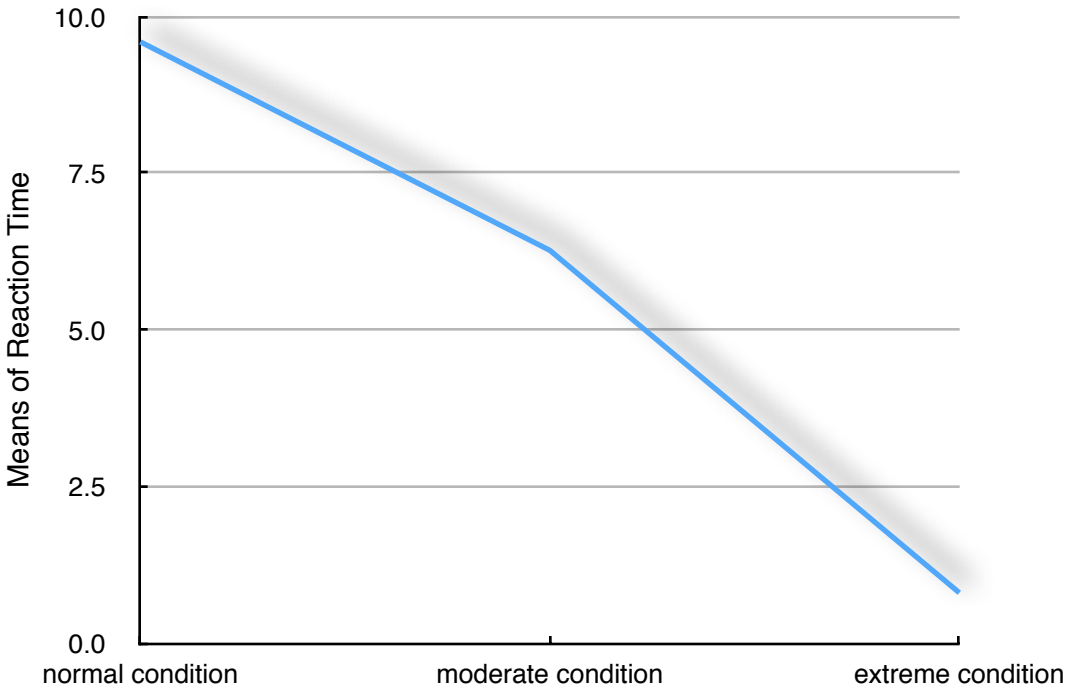

Figure C.5 Comparison of the mean values for estimated parameter RT.

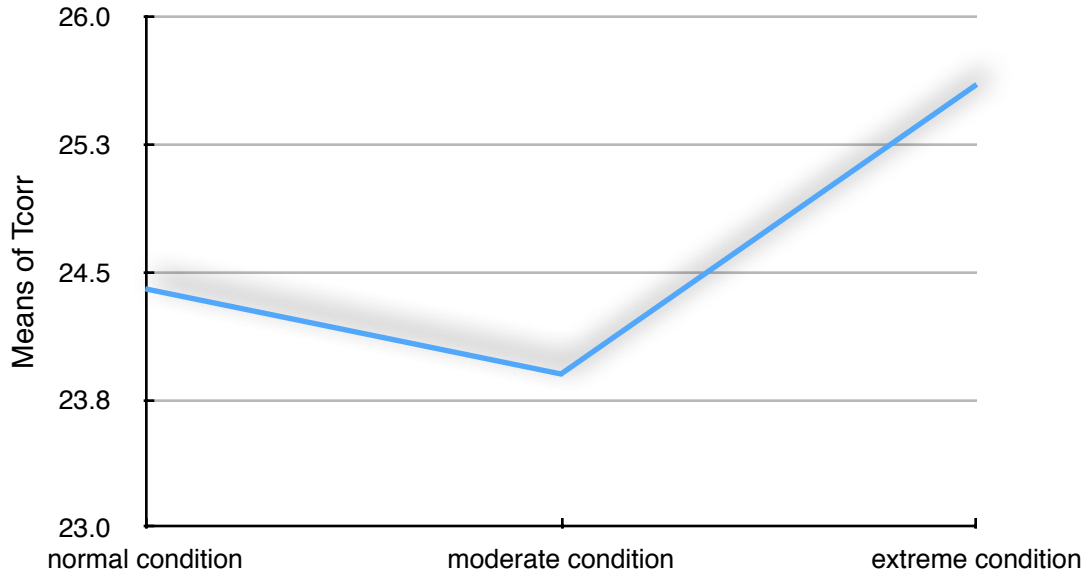

Figure C.6 Comparison of the mean values for estimated parameter τ_{corr}.

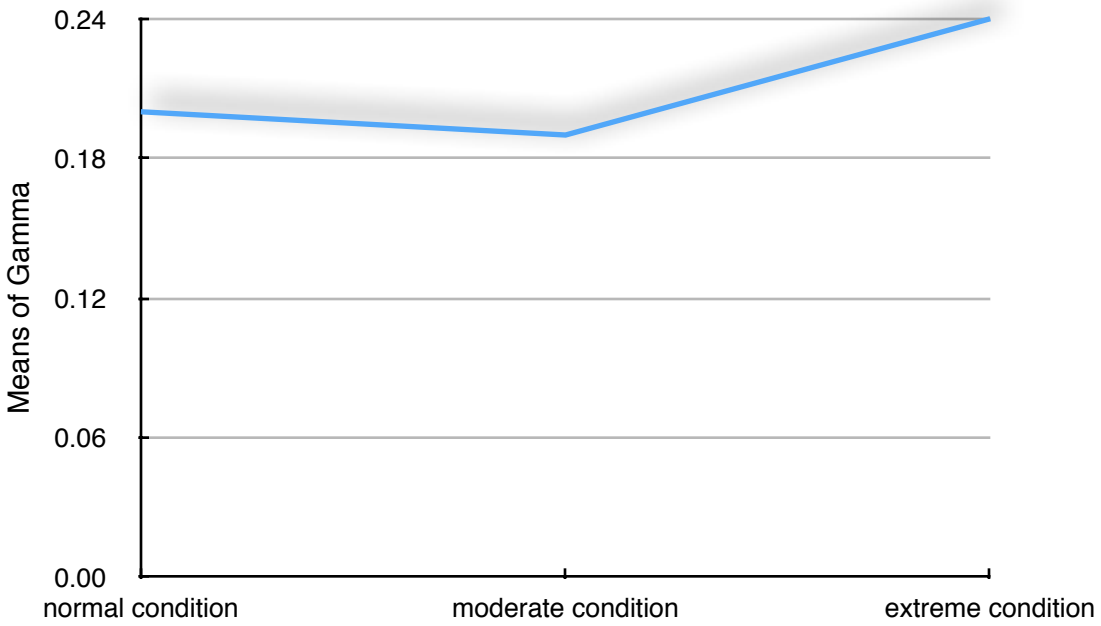

Figure C.7 Comparison of the mean values for estimated parameter W_c.

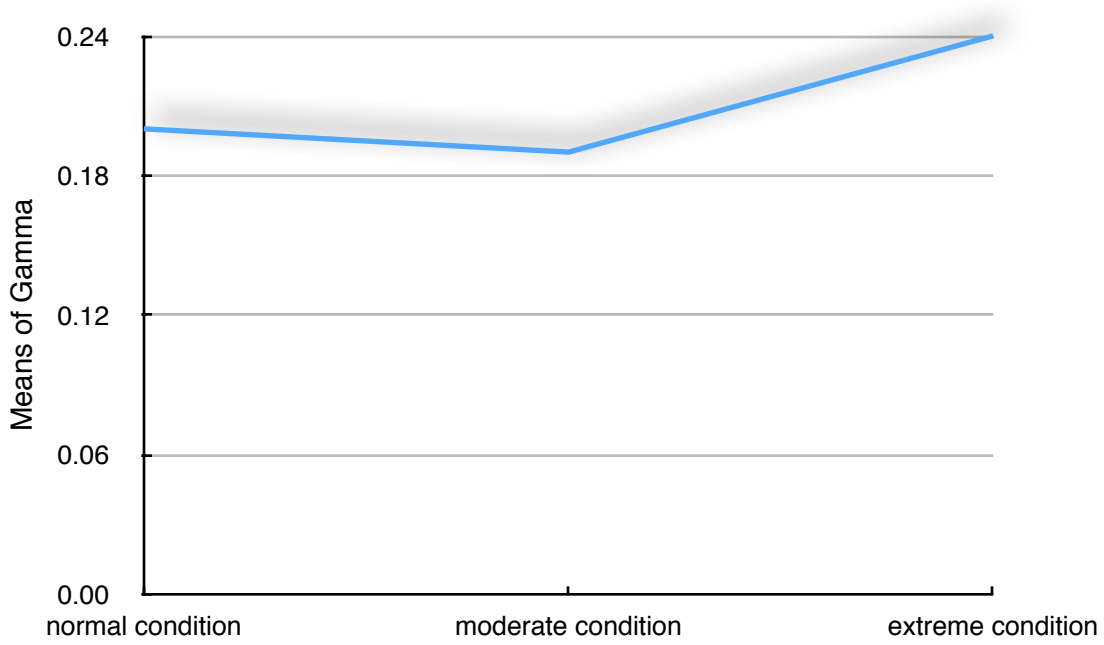

Figure C.8 Comparison of the mean values for estimated parameter γ .

APPENDIX D

The calculated PT function and total utility function values for the parameters represented in tables 5.3 to 5.5 are plotted in this section. This set of graphs demonstrate a comparison between calculated utilities using estimated parameters averaged over scenarios with only one common characteristic (independent variable). The observed differences in this approach are not as significant as in the first three groups (i.e., different challenge levels represented in chapter 5). It should be noted that the first approach is a more extensive approach since it takes into account all the external variables and the entire environment that they create.

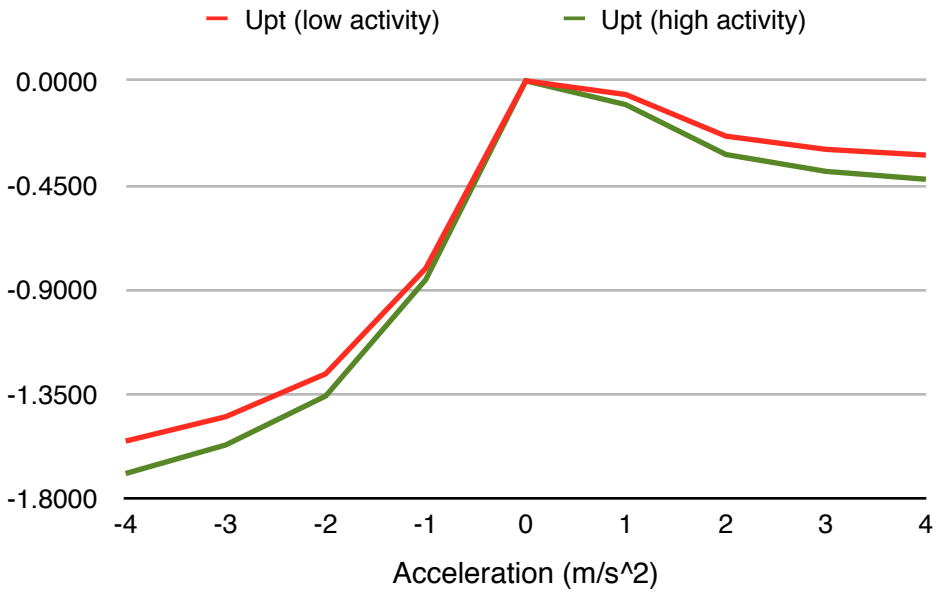

Figure D.1 Prospect Value (Equation 3.1) for different acceleration candidates with estimated parameters of table (5.5)

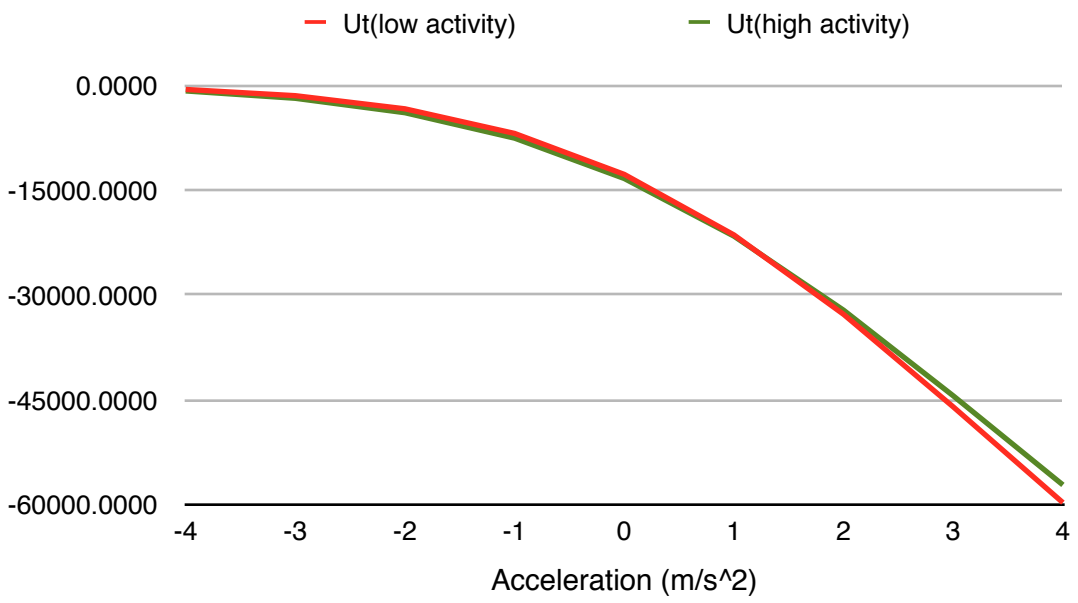

Figure D.2 Utility (Equation 3.2) for S = 30 m, V=40 miles/hour, deltaV=10 miles/hour with estimated parameters of table (5.5)

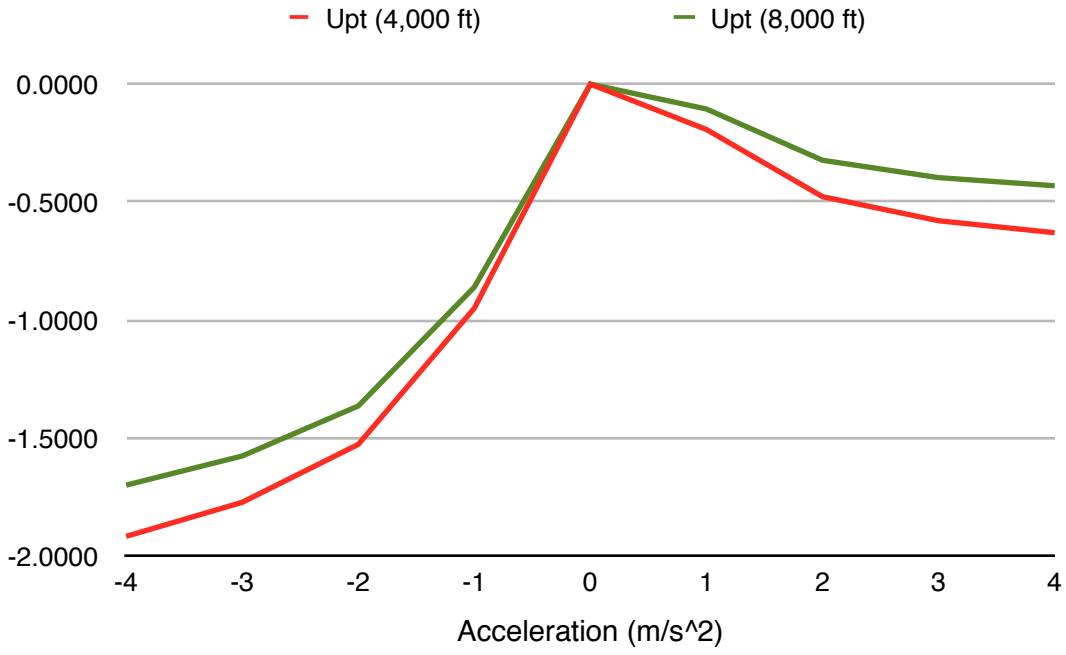

Figure D.3 Prospect Value (Equation 3.1) for different acceleration candidates with estimated parameters of table (5.3)

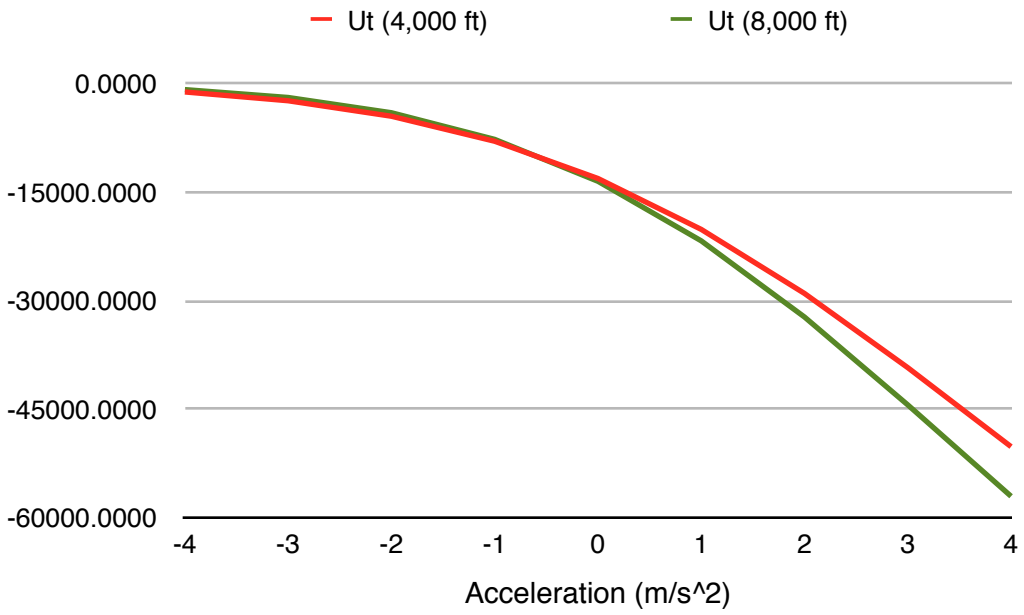

Figure D.4 Utility (Equation 3.2) for S = 30 m, V=40 miles/hour, deltaV=10 miles/hour with estimated parameters of table (5.3)

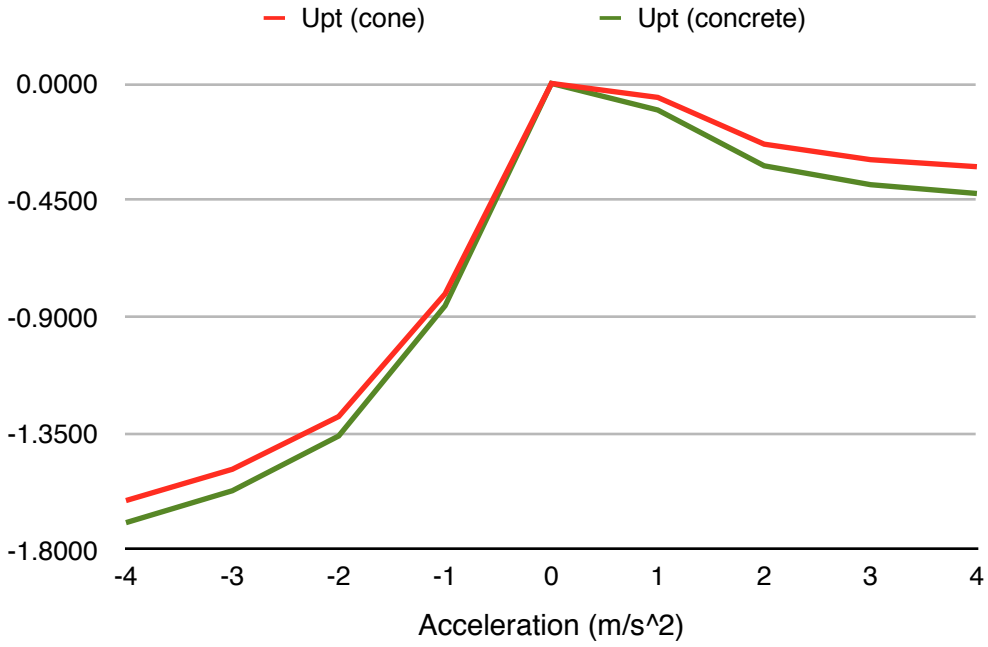

Figure D.5 Prospect Value (Equation 3.1) for different acceleration candidates with estimated parameters of table (5.4)

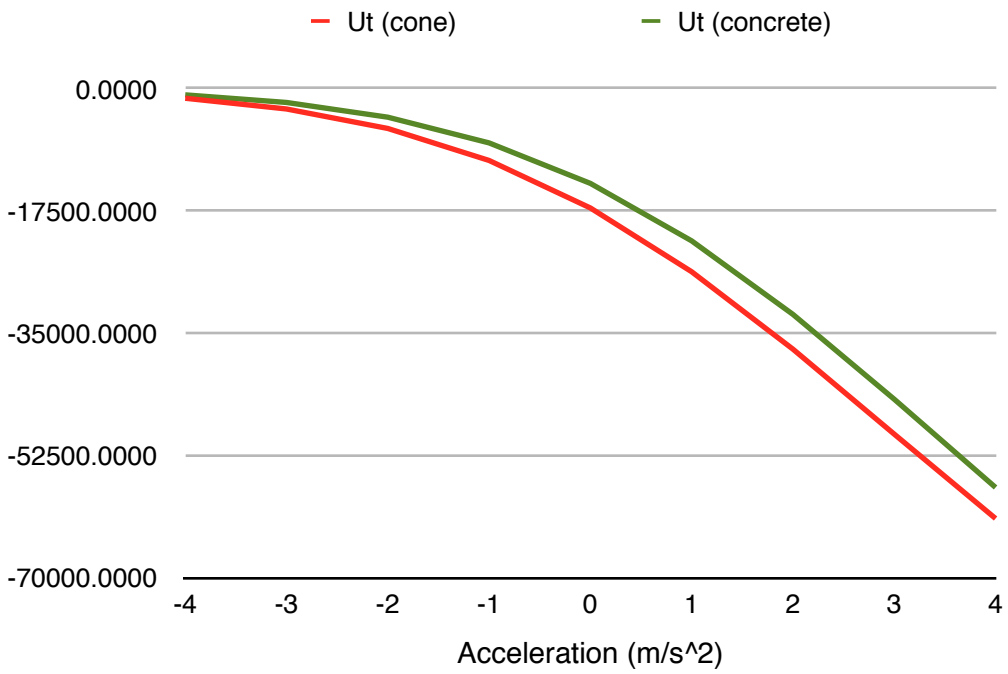

Figure D.6 Utility (Equation 3.2) for S = 30 m, V=40 miles/hour, deltaV=10 miles/hour with estimated parameters of table (5.4)