2011

Modeling Driving Behavior at Traffic Control Devices

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Modeling driving behavior at traffic control devices

by

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A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of
DOCTOR OF PHILOSOPHY

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Iowa State University
Ames, Iowa
2011

Disclaimer

This document was used in partial fulfillment of the requirements set forth by Iowa State University for the degree of Doctorate of philosophy. The numerical results and conclusions made in this report are interim steps and should not reflect the final and / or current views of Institute for Transportation or Iowa State University (ISU). The findings are restricted to the given vehicle, environmental conditions, routes, drivers and operation conditions.

Dedication

To those who under all circumstances are wishing others well.

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List of Terms and Abbreviations

AWS: All way stop

CO: Carbon monoxide

Emissions: NO_x, HC, CO, CO_2 and PM

CO_2: Carbon dioxide

DOE: United States Department of Energy

Driving behavior: state of speed, acceleration and gear choice of a driver in a given vehicle. Other phrases with similar meaning used in the dissertation are driving style and driving pattern

EPA: United States Environmental protection agency

Emissions: NO_x, HC, CO, CO_2 and PM

HC: Hydro-carbons

IEA: International Energy Agency

MANOVA: Multivariate analysis of variance

NO_x : Oxides of nitrogen

PEMS: Portable emission measurement system

PM: Particulate matter

VSP: Vehicle specific power (W/kg)

Traffic devices: Traffic control devices (all way stop, roundabout, traffic signal, sometimes curves)

TS: Traffic Signal

RDA Roundabout

On-ramp: Freeway entrance ramps

RPM: revolutions per second (engine speed)

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Acknowledgement

I would like to express my gratitude to Dr. Shauna Hallmark, my major professor who helped me in every aspect of my dissertation. Her guidance helped me to do my work in accordance with educational ethics and laws. Thanks are due to Dr. Gkritza and Dr. Cariquirry for helping with statistical analysis. I am grateful to Dr. Kasthurirangan Gopalakrishnan who provided continued guidance on my dissertation.

I would like to thank the staff at CTRE and the department of CCEE for providing the necessary support to complete this work. The environment at CTRE was very conducive for carrying out my research. Special thanks are due to Dr. Khaitan, Dr. Krishanan, Dr. Agrawal, Dr. Pande, Dr. Koundinya, Dr. Hazaree, Sidharath, Sparsh and Sandeep for their continuous encouragement resulting in timely completion of this work. I would also take the opportunity to thank Maria and Massiel for helping with statistics. I would like to express my gratitude to late Dennis Kroeger for helping with learning data collection. I would like to acknowledge Eliza, and Chris helping with technical writing.

Special thanks are due the drivers Ganesh, Nick, Bo, Nicole, Evan, Corey, Huishan, Jeff, Steve, Carlos, Ryan, AJ, Will and Mike.

I would also like to thank my parents, brother and sisters for providing me with the moral support I needed to consistently work on my research. Above all, I am indebted to my teacher, who has taught me the purpose of being an engineer and a responsible human being. His unceasing encouragement and loving support has made this work a success.

Abstract

Transportation is a major source of many major air pollutants as well as greenhouse gas emissions. The four common factors responsible for vehicular emissions are vehicle, road characteristics, traffic conditions and driving behavior. The objective of this dissertation was to study driving behavior since it is highly correlated to emissions as shown by previous studies. Understanding driving behavior is likely to help improve emissions estimates. In this dissertation, three levels of analyses of driving behavior were conducted including: (1) exploring driving behavior parameters and assessing their impact on emissions, (2) comparing driving behavior among the three most common traffic control devices, and (3) modeling second-by-second driving behavior of individual drivers. In order to explore these relationships, spatial location, vehicle kinematics, and CO_2 emissions were collected along a study road corridor in Urbandale (IA) was. The chosen road corridor comprised of a roundabout, an all-way-stop and a traffic signal along with curve and tangent sections. The traffic during peak and off-peak hours on the corridor was comparable. This was useful for comparing driving behavior across drivers under similar conditions. A single instrumented vehicle was driven over the corridor by four different subject drivers. The vehicle was equipped with a portable emissions measurement device which had engine sensor, tail-pipe sample lines and a GPS.

In the first analysis, vehicle kinematic variables were used to derive driving behavior parameters that included gas pedal use and brake pedal use. Two groups of drivers were identified based on these parameters. The study identified gaspad and brakepad as important driving behavior parameters which can explain variation in vehicular emissions.

Driving behavior parameters used in previous studies for developing driving cycle were utilized in this study to compare driving behavior between traffic control devices for the second analysis. These parameters characterized speed behavior, speed change behavior and energy gain behavior. A MANOVA model was used for comparing the overall driving behavior between traffic control devices by comparing these parameters. Results showed that driving behavior at the roundabout and all-way-stop differ significantly ($p < 0.001$) on at least one of driving behavior parameter. Likewise, roundabout and traffic signals also differed in terms of driving behavior ($p < 0.001$). Driving behavior and emissions are highly correlated. This implies using separate emission factors for different traffic control devices.

In the third analysis, speed profiles at roundabout were modeled for the drivers using a fourth degree polynomial regression. Results showed that speed profiles models were significantly different across drivers. This implied that drivers must be treated as random variables in modeling driving behavior and emissions for a given road or driver population. Average speeds of drivers at yield point were simulated based on the model. The maximum difference was found to be about 1.5 mph.

Keywords: vehicle kinematics, driving behavior, traffic control devices, emissions, polynomial regression, Bayesian hierarchical models, MANOVA.

CHAPTER 1. Introduction

1.1 Background

The transportation sector generates approximately 30% of the greenhouse gas (GHG) emissions in the U.S. Total mass of CO_2 (a GHG) emissions from the transportation sector (fuel combustion) was calculated as 4399 metric tons in 1990 and is estimated to double (9092 metric tons) by 2030 (IEA, 2011). Although this includes all modes, highway vehicles consisting of large trucks and passenger vehicles contribute a majority of it. The number of passenger cars is expected to be two billion in the next 20 years (Sperling and Gordon, 2009).

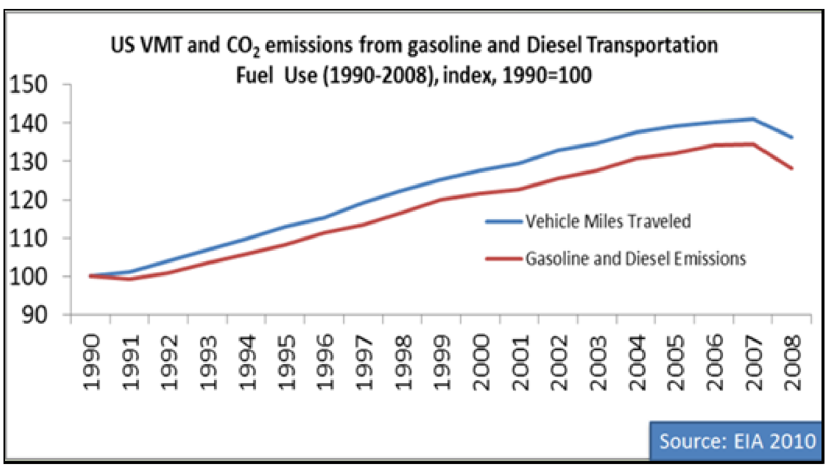

Figure 1.1: Increasing trend of VMT and corresponding CO_2 emissions

Many solutions have been proposed for changing the course of this present trend of vehicle miles travelled (VMT) and emissions. These include (1) using alternative modes of transportation such as transit or bicycling, (2) reducing vehicle miles traveled and number of trips, (3) using renewable fuels and alternative vehicle technologies, and (4) changing driving style/behavior.

Each solution has been demonstrated to be effective, but an interdisciplinary approach which combines these solutions is more likely to address GHG emissions from transportation. Apart from using technology, human behavior (needs and culture) plays an important role in solving the global problems caused by vehicular emissions, implying a need for change in human driving behavior (O'Brain, 2008).

Understanding the impact of driving on emissions is essential to develop appropriate strategies and policies pertaining to environmental-friendly driving. There are a number of factors that characterize driving either directly or indirectly, some of which are presented in the following section.

1.2 Factors affecting emissions

Cappiello et al., (2002) classified factors affecting emissions into four broad groups – vehicle technology specifications (Weight, emissions control devices, engine power specification), vehicle status (mileage, age, and mechanical status), vehicle operating conditions (power demand, air-fuel ratio, vehicle kinematics), and external environment conditions (air conditions, ambient temperature, road characteristics).

Vehicle operation is a result of how a driver chooses to drive a given vehicle. Aggressive driving may contribute to 40% higher fuel consumption as compared to normal driving, andemissions may be still higher (De Vlierger et al., 2000; Brundell-Freij et al., 2005). Further, research indicates that a single "hard “acceleration event may cause as much pollution as the rest of the trip (Guensler, 1993). Such findings have led to the adoption of environmental friendly driving habits, some of which are presented in the next section.

1.3 Eco-driving

Eco-driving strategies pertain to driving in a more environment friendly manner in order to reduce fuel consumption and emissions. According to eco-driving practices, small changes in driving style can affect big overall savings in energy use and lowering fuel consumption and emissions. Aggressive driving (speeding and braking) can lower gas mileage by about 33 % on a highway and 5% on an urban road. For most vehicles, an optimum speed at which fuel economy is highest is in the range of 35 to 55 mph (EPA, 2010). Each five mph above 60 mph can reduce fuel economy by 7%. Fuel economy is highly correlated to emissions.

Optimizing driving habits can help reduce emissions and fuel consumption. Nissan introduced the world's first eco-pedal to help reduce fuel consumption. They identified an unfavorable region of acceleration where the emissions are significantly high. An eco-pedal restricts the free flow pushing of the gas pedal and keeps the acceleration under a limit thereby checking the emissions. In essence, it helps in smooth acceleration. When high acceleration is needed, it is provided gradually. Nissan's internal research shows that driving with eco-pedal is likely to reduce fuel consumption by 5-10% (Nissan, 2008). Based on the many research findings on impact of driving on emissions and fuel consumption, several programs have been initiated to propagate eco-driving. The examples include,

1.) EcoDriving USA (EcoDriving, 2011),
2.) Driving Change (Hickenlooper, 2011), and
3.) GreenRoad (GreenRoad, 2011)

These programs have been in effect for a while and claim to reduce fuel consumption and carbon foot prints to the environment. The efficient driving habits include:

1.) Reducing idling
2.) Driving at speed close to speed limit
3.) Avoiding sudden hard accelerations
4.) Adopting smooth starts and stops
5.) Avoiding as much travel during off-peak hours as possible
6.) Taking the shortest route with the best roads
7.) Using cruise control
8.) Maintaining tires at the recommended air pressure
9.) Removing unwanted things from the vehicle to reduce its weight

The driver's behavior at a given traffic or road condition is generally termed as driving behavior (or driver behavior). The next section elaborates on this further.

1.4 Driving behavior

Driving behavior is defined as any parameter or group of parameters, combination, their derivatives or transformations that characterize the choice of speed, acceleration and gear by a driver to accomplish the driving task (Ericsson, 2005). It can also be stated as an attitude manifested in terms of acceleration, braking, cornering, lane handling and speed handling (Greenroad, 2011). Transportation activities are identified on a micro-scale level as driving behavior in this study. To implement appropriate strategies and policies that can help in reducing emissions, it is essential to understand and model emissions as a function of transportation activities or driving behavior.

1.5 Motivation for this work

The science of transportation of people and goods is an interdisciplinary subject. Vehicular emissions depend on the road characteristics, driving behavior and the vehicle. These factors are repeatedly being studied by transportation professionals, human factor researchers and vehicle manufacturers.

The present research is aimed towards studying the effect of traffic control devices and driving behavior on vehicular emissions and fuel economy at micro-scale level. Good understanding of the impact of driving style on emissions would improve existing driving style education programs (Mierlo et al., 2004). Although, aggregate comparisons have been made (Holmén and Niemeier, 1998) across drivers, previous researchers have not modeled driving behavior on a micro-scale level (second-by-second). This research is aimed towards modeling driving behavior on second-to-second basis. Understanding driving behavior at micro-scale level is likely to improve instantaneous emission models which are based on aggregate measures.

Also, researchers have not compared traffic control devices in the light of driving behavior parameters that affect emissions. A comparative study of driving behavior at most common traffic control devices is the focus of this research. This is likely to enhance modeling emissions at individual traffic control devices. The following section presents objectives that served accomplish the purpose of this research study.

1.6 Research objectives and problem statement

The analysis presented in this research was done on three levels namely (1) parameter-level, (2) intersection level, and (3) second-by-second level. The objectives underlying these analyses are stated below.

1.) To explore existing and proposed parameters in terms of drivers and traffic control devices.

2.) To compare driving behavior exhibited at different traffic control devices.

3.) To model and compare driving behavior of individual drivers on micro-scale level (second-to-second basis). This objective was motivated by finding a unique driving behavior model that can represent a typical driver. A driving behavior model can be highly useful in quantifying emissions at a given traffic control device.

1.7 Research scope

The study explored driving behaviors corresponding to a mid-size passenger car on the level of trips, traffic intersections, and a given geographical co-ordinate. The driving behavior of four different drivers was studied in terms of various parameters that affected vehicular emissions.

The research would help understand driving behavior and emissions at individual traffic intersections. This would improve the present emissions models and emission estimates and help in developing appropriate strategies for controlling emissions.

1.8 Organization of this dissertation

The dissertation is divided into seven chapters. The first Chapter introduces the background of the research, factors affecting emissions, driving behavior and emissions. It further describes the motivation and the research objectives and presents the scope of this work. The second chapter summarizes previous research on driver behavior and emissions analysis as well as emissions at different traffic devices. Chapter three contains data collection methodology, study design and data preparation. Chapter four presents an exploratory study on driving behavior parameters. Chapter five compares driving behavior across various traffic control devices. In chapter six, individual driving behaviors are modeled and compared across drivers. The last chapter (seven) summarizes the findings and contributions of this study, discusses the assumptions, explains the limitations and challenges faced, and presents recommendations for future research.

CHAPTER 2. Literature Review

This chapter summarizes studies on various aspects of driving behavior and its relationship to emissions. In addition, driving behavior and emissions specific to traffic control devices are also discussed.

2.1 Driving behavior and emissions

This section presents studies that correlate driving behavior with emissions. Past researchers have shown that driving behavior (or vehicle operating mode) directly affects the power required to operate a vehicle at a given state. Fuel consumption is highly correlated to emissions. The higher the power demanded of the engine, the higher is the fuel combustion leading to higher vehicular emissions. Emissions measured by a portable emissions monitoring system (PEMS) have high variability from one run to another due to factors such as engine condition, environmental condition and driving behavior (Rouphail et al., 2001). Understanding and modeling driving behavior is likely to help researchers in evaluating emissions more accurately and help in making appropriate policies for controlling vehicular emissions.

Evans (1979) studied the effect of driver behavior on fuel consumption on urban roads. Nine drivers including one with considerable experience and expertise in minimizing fuel consumption were asked to drive on a route with vehicle equipped with vacuum gauge fuel economy meter. The meter was divided into three regions namely green, orange and red which indicated increased level of power use or fuel consumption. The objective of the research was to contrast change in driving behavior due to traffic conditions and change due to individual driving style. In order to capture specific driving behaviors, the subject drivers were given seven instructions as stated below. They were asked to perform the following task.

1) Drive as they would do under normal conditions
2) Minimize trip time
3) Use vigorous acceleration and deceleration
4) Minimize fuel consumption by taking feedback from the fuel meter placed in the dashboard area
5) Maintain fuel economy meter in green region
6) Maintain fuel economy meter in green or orange region, and
7) Drive like a hypothetical, very cautious driver

The researcher found that for every 1% increment in trip time, the fuel consumption increased by about 1.1 %. Research showed that expert drivers can save fuel without changing trip time by making adjustments to their driving behavior in term of maintaining a particular speed and acceleration. The researcher also found it challenging to develop a 'perfect' fuel meter that would enable the driver to achieve optimum fuel economy in real-time.

Wang et al. (2008) studied driving behavior and developed driving cycle for Chinese cities. Driving cycle, as mentioned earlier, is a standard speed profile, which represents typical driving behavior for a given road class and drivers. Eleven cities of various sizes and geographical locations were selected for the study. On-road speed profiles were recorded using car chase technique on freeways, arterials and local roads. Professional drivers were asked to follow traffic in specific routes. The vehicle used was instrumented with a GPS and a speed sensor. Two sets of equipment were used to ensure high quality data. Data were collected during morning peak hours (7:30–9:00), afternoon off-peak hours (11:00–13:00), and evening peak hours (17:00–18:30). To estimate the characteristic of the entire traffic, the authors derived traffic adjustment factors based on road type, peak hours, traffic volume, road length and average speed on the road. Eleven driving behavior parameters were derived from the time-speed traces. These include (1) average speed, (2) average running speed (average speed after removing idling events), (3) average acceleration ,(4) average deceleration, (5) percent of time in idling mode, (6) percent of time in accelerating, (7), percentage of time cruising, (8) percent of time in decelerating, (9) relative positive acceleration, (10) positive acceleration kinetic energy, and (10) the frequency of decelerating phase after an acceleration phase for every 100 meter driven. Vehicle driving pattern was found to be dependent on the size of city, local road characteristics and individual driving behavior. The driving behavior pertaining to Chinese cities was found to be significantly different from the driving behavior corresponding to European and US driving cycles. This entails that driving cycle for European and US driving cycle cannot be used for characterizing driving behavior in Chinese cities including the large ones. Based on the longer duration of cruising and acceleration mode (over 83%), it was found that driving in Shanghai, China and Chengdu, China involved high percentage of acceleration and hard brakes. Shanghai and Chengdu were also associated with aggressive driving as depicted by high acceleration and deceleration measurements. Driving in small Chinese cities was found to be less aggressive.

Holmén and Niemeier (1998) conducted a field study of 24 drivers to study the effect of acceleration events on real-world vehicle emissions. They found that the variability associated with driving behavior produced significantly different tail pipe emissions. There were significant variations in CO and NO_x emissions among the 24 drivers under similar test route, traffic density and vehicle type. They found that driving patterns were dependent on the intensity of vehicle operation within a given mode.

Ericsson (2000) studied the variability in urban driving behavior in light of driver, street environment and traffic conditions. Twelve university employees were chosen to drive a car instrumented with a data-logger that registered vehicle speed every $1/10^{th}$ of a second. The route consisted of a loop from a residential area to the city center and back on the same road. Street type, peak hour/off-peak hour and gender were considered as fixed effects while driver was taken as a random factor. The driving behavior of each driver was assessed using 26 parameters divided into three categories namely level measures, oscillation measures and distribution measures. Level measures consisted of means and standard deviations of speed and acceleration. Oscillation measures comprised of relative positive acceleration (RPA) and the frequency of occurrence of a particular ratio of maximum speed to min speed. On the other hand, distribution measures consisted of various intervals of speed, acceleration and deceleration. The marginal effect of each of the driving behavior parameters were studied for driver, street environment and traffic conditions (peak/off-peak hours). The study was conducted to compare driving behavior between and within different street types, drivers and traffic conditions. Driving behavior showed very significant differences between street type and driver for in terms of all parameters. The effect of street type was generally higher than the driver effect. Average speed and average deceleration were found to lower at peak hour conditions. Men were found to drive at higher average acceleration levels. According to the researcher, the most important driving behavior parameters were relative positive acceleration, frequency of occurrence of maximum speed/minimum speed to be greater than 2 per 100 m, percentage of time when acceleration exceed 1.5 m/s^2, percentage of time when deceleration was about -1.5 to -2.5 m/s^2, and percentage of time speed below 15 km/h (~ 10 mph).

Ericsson (2001) attempted to find independent driving behavior parameters that can explain a large variability in emissions and fuel consumption. To collect vehicle activity and driving behavior data, five passenger cars of different sizes and performances were equipped with a data-logger and driven on roads in an average sized Swedish city. A total of 2550 journeys and 18945 km of data were collected. Subject drivers were chosen from 30 families in the city of Vasteras, Sweden. As revealed by the families, 45 different drivers drove the vehicles. Driving behavior was attributed to street type, street function, street width, traffic flow and codes for location in city (central, semi-central, peripheral). A total of 62 different driving behavior parameters were defined depending on which of the attributed values changed. These parameters measure distribution of speed, acceleration and deceleration, occurrence of stops, maximum speed/minimum speed, duration of time driving at a given gear, and vehicle power. The researcher found that many of the driving behavior parameters are correlated. Factor analysis was performed, which reduced the number of parameters to 16 independent measures which the researcher called typical parameters. Factor analysis is a method of constructing new variables from the linear combination of the original variables such that the new variables have negligible correlation among them. Emissions and fuel consumption were estimated for the chosen vehicles using Swedish emissions models (VETO Rototest models). The estimated emissions and fuel consumption were then modeled using regression on the typical factors. Of the sixteen factors, nine factors pertaining to power demand, gear-changing pattern and certain speed range had considerable effect on emissions. Specifically, fuel consumption was affected by factors corresponding to high and moderate power demand, stops, speed oscillation, extreme acceleration, and high speed and moderate speed at gear two and three. Emissions of HC were primarily dependent on acceleration with high power demand and extreme acceleration. NO_x emissions were mainly affected by acceleration with high power demand, extreme acceleration, engine speed > 3500 rpm and late gear changing from gears two and three.

Nam et al. (2003) compared real-world CO, THC (C_3H_8), NO, and CO_2 emissions with modeled estimates at different driver aggressiveness. The authors used a PEMS to measure real-time emissions (above gases), travel times and vehicle kinematics through a busy road network in southeast Michigan. Emissions were also estimated using an integrated framework of Comprehensive Modal Emissions Modal (CMEM) and a microscopic traffic model VISSIM. The emissions model was calibrated with on-road data using a dynamometer. The researchers used root mean square of power factor (2*speed*acceleration) as a measure of driver *aggresivity*. For each trip, driver aggresivity was computed. They found that aggressive driving produced significantly higher emissions as shown in Table 2.1.

Table 2.1: Emissions for normal and aggressive driving (Nam et al., 2003)

	Measurement		Model estimates
Driving	Normal	Aggressive	VISSIM
Travel time (sec)	1011	1031	974
Aggressivity ($kmph^2/s$)	95.7	116.1	83.4
Fuel (g/mile)	154	165.1	135.5
CO_2 (g/mile)	488.7	521.4	428.9
CO (g/mile)	0.25	2.00	0.41
HC*100 (g/mile)	0.04	2.41	0.89
NOx (g/mile)	0.52	0.67	0.31

Wahab et al. (2007) studied brake pedal and gas pedal pressure of the driver to understand the driver behavior under different environmental conditions. The driving data was taken from In-car Signal Corpus hosted in Center for Integrated Acoustic Information Research (CIAIR), Nagoya University, Japan. Stop-and-go-segments were extracted since they contain a good percentage of acceleration and deceleration behaviors. New parameters were derived by taking the first derivatives of gas pedal pressure and brake pedal pressure. The researcher used four driving behavior parameters for analysis. These parameters, brake pedal and gas pedal pressure and their derivatives, were transformed to frequency domain by deriving the power spectral density. The authors used Gaussian mixture models (GMM) to analyze the brake and gas pedal pressure plots (mesh and contour plots) of the individual drivers. They found that these plots were unique for each driver proposed that this method can be extended to predict sequences of individual driving behaviors. Driving behavior parameters in various studies is listed in Table 2.2 along with reasons why they are important.

Table 2.2: Driving Parameters from literature

Driving Parameters	Why are they important?	References
Mean speed	Central tendency of motion	(Kuhler and Karsens,1978)
Mean driving speed	Central tendency of motion	(Kuhler and Karsens,1978; André,1996)
Mean acceleration	Acceleration behavior	(Kuhler and Karsens,1978)
Mean deceleration	Deceleration behavior	(Kuhler and Karsens,1978)
Mean driving duration	Average speed maintained	(Kuhler and Karsens,1978; André,1996)
Mean number of acceleration and deceleration changes in a trip	frequency of brake pedal and gas pedal use	(Kuhler and Karsens,1978; André,1996)
Proportion of stand still time ($v < 3$ km/h, $\|a\| < 0.1$ m/s2)	Correlated with duration of idling	(Kuhler and Karsens,1978)
Proportion of acceleration time	Frequency of acceleration	(Kuhler and Karsens,1978)
Proportion of deceleration time	Frequency of acceleration	(Kuhler and Karsens,1978)
Acceleration standard deviation	Change in frequency of acceleration	(André,1996)
Positive kinetic energy	Vehicle energy demand	(André,1996)
Number of stops per km	Number of acceleration and deceleration phases	(André,1996)
Relative and joint distribution of speed, acceleration and deceleration	Adaptation to maintain a given speed and acceleration	(André,1996)

Inertial power (acceleration x speed)	Adaptation to overcome drag force	(Fomunung et al. ,1999)
Drag power (acceleration x speed2)	Found to be highly correlated with me and fuel consumption for heavy duty vehicles	(NAP, 2000)
Relative positive acceleration	Measure of stress taken by the engine	(Weijer,1997; Mierlo, et al.,2004; Ericsson, 2000)
RPM	Central tendency of motion	(Mierlo, et al.,2004)

2.1.1 Summary (Driving behavior and emissions)

Vehicular emissions are found to be highly dependent on how much energy (in the form of fuel combustion) is demanded of the engine. Amount of emissions are dependent on diver activities as quantified by the four common driving modes namely – cruise, idling, acceleration and deceleration. Studies outlined above shows that emissions is highly correlated to driving behavior. High speed and acceleration mode are especially responsible for peak emissions. Several driving behavior parameters have been utilized in the literature to explain driving behavior.

2.2 Emissions at various traffic control devices

Emissions at a road intersection were found to be significantly higher than that at mid-block sections of the road. This is because intersections tend to make drivers slow down or stop. This entails the driver to accelerate to attain the flow speed. The following studies quantify and compare emissions at traffic intersections.

Ahn el al. (2009) evaluated the energy and environmental impacts of installing a roundabout, all-way-stop, or a traffic signal at an intersection that was an alternative access point to Washington Dulles Airport. The intersection experienced high traffic volume during peak hours. Through simulation, the researchers compared emissions at the traffic intersection by assuming it to be either a roundabout, a stop control (two way stop control) or a traffic signal. They used INTEGRATION and VISSIM to simulate large number of deceleration and acceleration events corresponding to the three traffic control devices. The authors also estimated the second by second emissions and fuel consumption using VT-Micro model and the Comprehensive Modal Emissions Model (CMEM). The roundabout was found to be efficient as long as the traffic demand increased by 50 percent. However, beyond that, the roundabout produced substantial increase in delay while traffic signal was most efficient. With VISSIM and VT-Micro model, fuel consumption was found to increase by 13 % and 8% when the stop sign control was substituted with proposed roundabout or a traffic signal, respectively. CMEM estimated that fuel consumption increased by 18% when stop sign control was replaced by a roundabout. The roundabout produced 155%, 203%, 38%, and 10% higher HC, CO, NO_x, and CO_2 emissions, respectively. On the other hand, HC, CO, NO_x, and CO_2 emissions increased by 80%, 108%, 28%, and 8% respectively at the traffic signal based on VT-Micro model estimates. According to CMEM model HC, CO, NOx, and CO_2 emissions increased by 344%, 456%, 95%, and 9%, respectively roundabout was installed instead of the stop control. Results also showed that increase in emissions and fuel consumption was greater for roundabout than for traffic signal.

Coelho, et al. (2006) studied the environmental impact of a single lane roundabouts located in Lisbon (Portugal) and Raleigh (North Carolina, US). They videotaped the site and extracted queue length, time gap between successive acceleration-deceleration cycles, and the number of times the vehicle stopped before entering the roundabout circle. Real-world speed profiles for typical stop and go conditions were obtained from repeated runs at several single lane roundabouts in the region of Lisbon. A microwave Doppler sensor was used for measuring entrance speed of various vehicles. The researchers recorded stop and go behavior, on-road emissions and synthesized speed profiles using traffic volume and conflicting volume (or circulating volume) which are correlated with queue length. Based on intensive empirical measurements the researchers identified three typical speed profiles (Figure 2.1) that can be observed at a roundabout. The probability of occurrence of each of the profiles was modeled using approaching traffic volume and circulating traffic volume. The proportion of time the vehicle experienced profile I, II and III were found to be 43%, 36% and 21% respectively. VSP was computed from speed profiles and then based on VSP bins and emissions lookup table (North Carolina State University, 2002; Frey et al., 2003) NO_x, HC, CO, CO_2 and PM emissions were estimated.

They found that the region of influence where vehicles accelerate back to free flow speed (after encountering traffic intersection) was important in terms of understanding its relative impact on total emissions. About 25 % of total emissions were found to have come from this region of acceleration. Emissions were found to increase monotonically with free flow speed (speed limit outside the influence of roundabout) beyond the region of acceleration. Emissions were found to increase as the difference between free flow speed and circulating speed became larger.

2.2.1 Summary (emissions at traffic control devices)

Previous research shows that emissions at various traffic control devices varied across traffic control devices. This is due to the difference in driving behavior when drivers try to adjust their speeds to traverse various sections of the road or intersections. It was also found that emissions at these traffic control devices were highly dependent on traffic conditions.

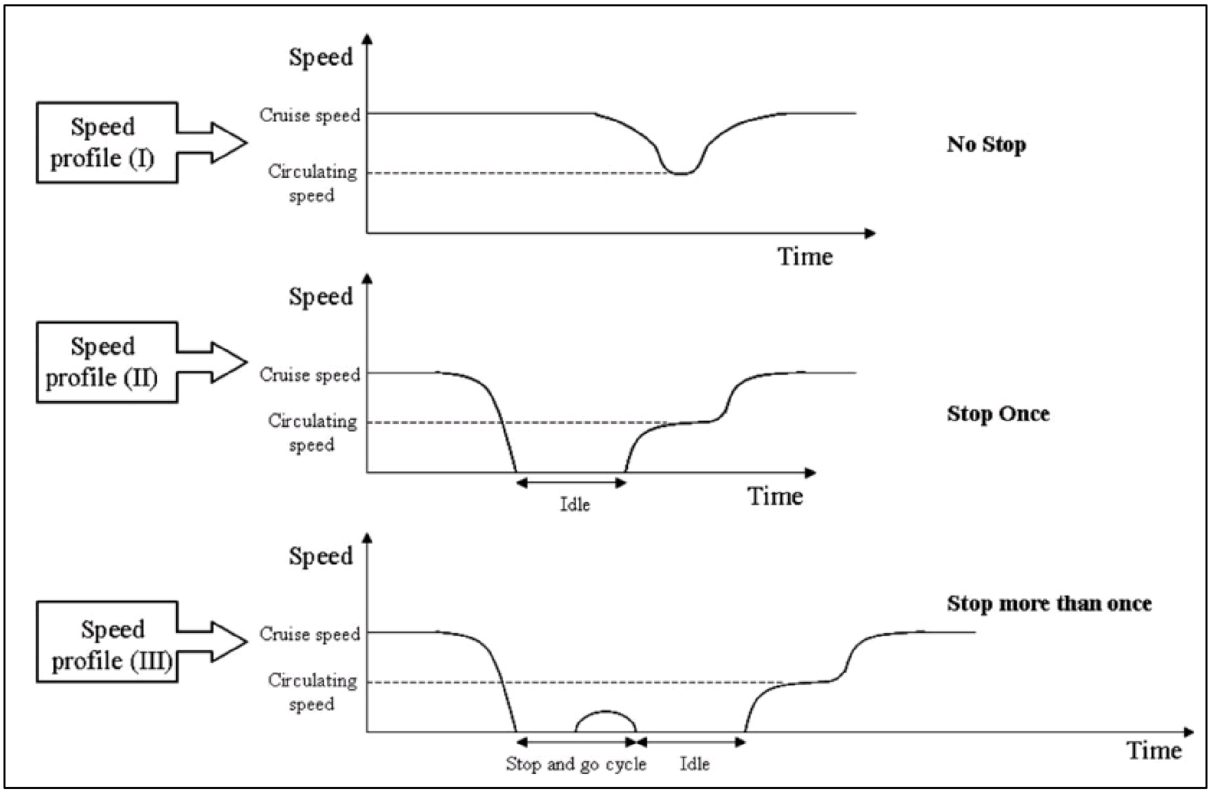

Figure 2.1: Typical speed profiles at a roundabout (Coelho, et al., 2006)

2.3 Contributions of the present study

This dissertation extends the finding and methods to study driving behavior across drivers and traffic control devices. Driving at a traffic control device is a characteristic of individual driving behavior. In this dissertation, we studied individual driving behavior at traffic control devices to closely examine its impact on emissions. Specifically, the dissertation has the following contributions.

1.) Wahab et al. (2007) quantified driving behavior by the amount of pressure the driver applied on the gas pedal and brake pedal. In this dissertation, this concept of gas pedal pressure and brake pedal pressure was used to study driving behavior and its impact on emissions. Variables quantifying gas pedal pressure and brake pedal pressure were derived from acceleration.

2.) Emissions at traffic intersections are significantly different from those at the mid-block sections of the road. Traffic control devices force the drivers to slow down (or stop) and then accelerate which results in higher emissions. Researchers have studied driving behavior and emissions for different road types (Ericsson, 2000) but they did not compare driving behavior across traffic control devices. Some studies compared emissions and fuel consumption but did not adequately explain how they are correlated to driving behavior at traffic control devices. In other words, this dissertation studies on driving behavior in the light of traffic control devices while taking the driver as a random variable.

3.) In general, studies have compared driving behavior of different drivers in terms of aggregate measures. In this dissertation, an attempt was made to compare driving behavior on a micro-scale (second-by-second) level. This is important for identifying hotspots where a typical driver or a certain group of driver operates the vehicle differently so as to produce significantly high emissions. Aggregation takes away the information on instantaneous driving behavior. Driving behavior of the overall trip tends to average out and details regarding acceleration and deceleration behavior are not well segregated. For example, we may consider a driver who accelerates hard to change lanes but slows down smoothly at the traffic control devices. Taking average value of such a trip tends to hide the high acceleration event. Instantaneous models require quantification of driving behavior at high resolution (in time and space). This dissertation, attempted to further the research by comparing driving behavior at roundabout, all-way-stop, and traffic signal. Driving behavior like acceleration and deceleration in terms of their duration and intensity can be well captured at the traffic intersections where it is unavoidable to observe these behaviors. This study modeled and compared speed profiles across drivers in order to validate the assumption that driving behavior differ across drivers and that the driver must be treated as a random variable.

CHAPTER 3. Data Collection and Data Preparation

3.1 Research outline and data collection

Data collection is a critical step in any research process since it is highly dependent on the objective of the study. The broad objective of the study was to explore driving behavior and emissions at traffic control devices: roundabout, all-way-stop, traffic signal. In order to achieve this objective, on-road emissions tests were performed and driving behavior of four drivers were measured and analyzed.

This chapter gives a detailed description of data collection procedures, and data preparation or preprocessing required for analyzing the collected data. The following section describes the data collection processes: selection of appropriate route, vehicle, instrument, and study period. This is followed by data preparation which comprised of extracting relevant information from the raw data, defining new variables, removing outliers and preparing the final data tables required for specific analysis in the upcoming chapters.

3.2 Data collection and study design

Vehicular emissions highly depend on the study period and traffic conditions (Ahn et al. 2002), test route (Ropkins et al., 2007), vehicle (Wenzel and Singer, 2000), and driver (Yu and Qiao, 2004). In addition, vehicular emissions are also affected by the type of traffic control device encountered at a traffic intersection (Coelho et al., 2006; Mandavilli et al., 2008; Ahn el al., 2009). Therefore, an appropriately chosen test period, test route, test vehicle and subject drivers are needed. The following sections elaborate on these important aspects of data collection protocol.

3.2.1 Study route

The study was aimed at understanding driving behavior at various traffic control devices. Several potential test sites were evaluated in this regard. Eventually, a corridor along Douglas Avenue (Urbandale, IA), a minor arterial, was chosen as the test route (Figure 3.1). This corridor was chosen as it has all the three traffic control devices in a row. The speed limit on the route was 35 mph except for the roundabout circle where it was 15 mph. Same speed limit throughout the route offered similar conditions for comparing driving behavior across traffic control devices. A pilot study was conducted on the chosen route, and this provided insight into the traffic and road environment the experiment drivers would encounter. Douglas Avenue runs east to west and passes over the interstate I-35 while connecting with it through a partial cloverleaf interchange.

The chosen corridor is a paved four-lane road (median separated) except on the west side of the all-way-stop where it changes to a two-lane road. The route is comprised of a traffic signal, a roundabout (radius ≈1780 ft.), an all-way-stop, curve section and a tangent section (length ≈1.62 miles). The length of the tangent section and curve section were 1.62 and 0.5 miles respectively. The total length of the test route was three miles.

Figure 3.1: The study route chosen for data collection (Map © 2011 Google)

To indicate different portions of driving, the following terms were defined.

1.) **Loop**: A loop of driving implied driving from the east end of the route to the west end and back.

2.) **Trip**: A trip was defined as driving from one end to another. A loop consisted of two trips.

3.) **Trip-part**: A trip-part denoted the portion of a trip that was in the region of influence of a traffic intersection or traffic control device.

The next section describes the vehicle and equipment used for data collection on the above test route.

3.2.2 Portable Emissions Monitoring System (PEMS)

In general, tail-pipe emissions can be measured using two methods namely on-road testing and dynamometer testing. The former entails instrumenting a vehicle and measuring the emissions while it is in-use on the road. The latter is a laboratory set up where the vehicle is made to mimic a standard speed/acceleration profile called driving cycle. This standard driving cycle is a sequence of many driving behavior events. It is a representative of driving behavior for a given vehicle and road type. A portable emissions monitoring system (PEMS) was used in this study for measuring and recording emissions and vehicle activity data. This equipment has the following advantages.

1.) **Time effective**: It can be hooked up in 20-30 minutes for hours of testing whereas using a dynamometer is time consuming. Setting up the equipment consists of connecting the PEMS to a power source (an external battery placed inside the moving vehicle), placing the sample probe in the exhaust, routing exhaust lines, and connecting on-board sensors to various locations of the engine.

2.) **Wider deployment**: A wide range of vehicles can be tested at reasonable cost and time. PEMS has been used on both on-road and off-road vehicles (Frey et al., 2005).

3.) **Testing various scenarios:** It measures real world driving pertaining to a specific road, vehicle and driver. For this reason the PEMS is helpful in identifying high emissions spots, in recording hard acceleration events, aggressive driving and other driving behaviors (Holmen et al., 1997; Nam et al., 2003; Yu and Qiao, 2004) on a second-to-second basis. It is also shown to be a good tool in assessing the impact of traffic control on emissions (Frey, 2000) or comparing emissions across different routes (Ropkins et al., 2007). The PEMS can also be an effective device in comparing emissions at different road grades (Frey et al., 1997) and in assessing the impact of transportation improvements on emissions (Rouphail et al., 2001; Unal et al., 2003).

Further, PEMS can also be used for testing renewable fuels or power sources (Frey et al. 2007).

With all the above advantages, however, PEMS data is comparatively less reliable for standardizing emission factors due to lack of repeatability. Dynamometer measurements are mandatory for quantifying emission factors and developing environmental policies. However, PEMS data when successfully validated using a dynamometer testing, can be very useful since it also records factors that affect emissions.

The PEMS (Figure 3.2) used in this study was the Axion system manufactured by Clean Air Technologies Inc. The emissions measured by the PEMS are hot-stabilized oxides of nitrogen (NO_x), hydrocarbon (HC), carbon monoxide (CO), carbon dioxide (CO_2) and particulate matters PM_{10}.

The PEMS records emissions and engine parameters (rpm, intake air temperature and manifold absolute pressure) along with geographic information (latitude, longitude, bearing and altitude) using a GPS. The emissions, the engine parameters and geographic information are synchronized on a second-to-second basis.

Concentration (mass/second) of emissions is estimated using engine-RPM, intake air temperature, manifold absolute pressure and mass of emissions per unit volume of the exhaust. This also takes into account the user-supplied fuel composition. The manifold absolute pressure transforms changes in engine speed and load into electrical signals which control the flow of fuel into the engine. Engine rpm and intake air temperature provide information on engine stress.

Figure 3.2: Axion (Portable Emissions Monitoring System, Source: www.cleanairt.com)

The system consists of two gas analyzers which alternatively perform zeroing – a method in which each analyzer calibrates itself with the ambient air away from the exhaust air. The values corresponding to the active (sampling from the tail pipe) analyzer are recorded. When both the analyzers are active, average values are logged.

We used PEMS for measuring vehicle activities and emissions on a single test vehicle which is discussed in next section.

3.2.3 Test vehicle

Emissions tests were conducted on a 2005 Ford Taurus, a mid-size passenger car. The test vehicle operated on gasoline with automatic transmission feature. The objective of the study was to understand driving behavior, and therefore it was assumed that each driver would drive any other mid-size passenger car in a similar manner. A single vehicle was used to reduce the possible variability in emissions due to the use of different vehicles (Frey et al, 2010). This test vehicle was driven by subject drivers who are described in the next section.

3.2.4 Subject drivers

Four graduate students at Iowa State University were chosen as subjects drivers for the study. Two were male and two female, and their age ranged from 20 to 25 years. Each had a minimum of three years of experience with driving and was familiar with US road and traffic conditions and regulations.

3.2.5 Data collection period

A total of four days of data were collected. This included morning and afternoon peak and off-peak hours. The morning and afternoon peak hours were assumed to be from 7 to 9 am and from 5 to 7 pm respectively. /The morning and afternoon off-peak hours were from 9 to 11 am and from 3 to 5 pm. Two drivers drove from 7 to 11 am on 13 and 20th April 2010 and the other two drove from 3 to7 pm on 7th and 14th April 2010. The data collection schedule is summarized in Table 3.1.

Table 3.1: Data collection schedule

	Morning peak	Morning off-peak	Afternoon peak	Afternoon off-peak
Date =>	13 and 20 April 2010		7 and 14 April 2010	
Time =>	7 to 9 am	9 to 11 am	3 to 5 pm	5 to 7 pm
Driver-1	X	X		
Driver-2	X	X		
Driver-3			X	X
Driver-4			X	X

3.3 Test protocol

On the day of data collection the vehicle was equipped with PEMS at the gas station located near the east end (shown as red balloon point A in Figure-3.1). Two of the four drivers and a data collector would sit in the car at driver and passenger seats respectively. A given driver would drive from the east end to the west end of the corridor and back thus completing a loop. After few loops of driving the subject drivers would switch places to prevent boredom and fatigue which may affect their natural driving. On an average, each driver made 25 trips. A total of 109 trips of data were collected. This comprised 16 hours of driving. The duties of the data collector included,

1.) Making sure that the PEMS was working normally and that it was fastened tight to the vehicle. While on the road, the PEMS is subjected to motion and vibrations which can lead to equipment malfunction and may also render the data invalid.

2.) Recording queue position while the drivers stopped and waited for their turn at the traffic intersections.

3.) Making a qualitative assessment of the traffic flow, and recording abnormal traffic conditions, if any.

Once the data were collected, these were preprocessed for analysis and interpretation. The next section deals with data preparation which includes data cleaning, variable extraction, and defining new variables.

3.4 Data preparation

PEMS provides raw data in the form of comma separated values (csv) files. The data were imported into Excel (2007). Some variables were in the form of strings and were therefore transformed to numbers. The data were processed and a quality assurance process was performed. The steps taken to address inappropriate data and to process the data into the final format for analysis are described below.

3.4.1 Eliminating unwanted columns in data sheet

In order to simplify the data processing and analysis, variables such as altitude, and those related to raw gas analyzers data were removed since they were not needed to meet the objective of this study.

3.4.2 Inserting categorical variables

In order to segregate observations corresponding to individual driver, trip number, date and time of testing and direction of travel, new categorical variables were defined for each spreadsheet file. These variables were “Driver”, “TripID”, “DT”, and “Dir”. PEMS records the bearing of the moving vehicle. The variable “Dir” implying direction of travel was obtained using the bearing values recorded by PEMS. A bearing of more than 180^{o} implied west bound.

3.4.3 Removing rows with abnormal observations

Some observations had negative and exceptionally high emissions values (e.g. > 100 g/s). Negative values may appear due to very low value of the given emissions, an error in the equipment (PEMS), or because of unusually high concentrations in the ambient air which was used as a baseline. Identification and removal of observations was performed in R (Version 2.11.1).

3.4.4 Defining new parameters and variables

Several new variables were created using existing variables as shown in Table 3.2. Acceleration was calculated as rate of change of speed. Jerk, the rate of change of acceleration, was used as a measure of hard acceleration. Jerk has been used by many researchers to quantify aggressive driving behavior (North et al., 2006; Bagdadi and Varheliyi, 2011). Vehicle specific power (VSP) is a function of speed, acceleration and road grade. It is shown to explain a good percentage of variability in emissions (Jiménez-Palacios, 1999; Frey, 2002; Nam, 2003). Two major emissions models namely MOVES and CMEM utilize VSP for characterizing emissions. Road grade was assumed to be zero on the given route. Therefore, in the present context VSP was only a function of speed and acceleration.

The variables gaspad and brakepad denoted the gas pedal use and brake pedal use respectively. These variables, computed from acceleration, were effective in segregating acceleration and deceleration behavior at a given second.

3.4.5 Data Merging

After cleaning the data and defining relevant variables, data from various drivers/trips/days were merged into a single datasheet for easy editing, querying and analyzing.

3.4.6 Assigning roadway and traffic control variables

The Manual on Uniform Traffic Control Devices (MUTCD) defines a traffic control device as “a sign, signal, marking, or other device used to regulate, warn, or guide traffic, placed on, over, or adjacent to a street, highway, pedestrian facility, or shared-use path by authority of a public agency having jurisdiction” (MUTCD, 2009)

In this dissertation, driving behaviors at the three traffic control devices namely roundabout (RDA), all-way-stop (AWS), and traffic signal (TS) were studied. A new variable called “TrafficD” was defined to indicate a traffic control device present at a given section of the route. This section called “region of influence” was identified using a GIS package (ArcMap 9.3).

On an average, the drivers entered a deceleration phase about 500 ft. upstream of a traffic control device. Similarly, drivers on an average utilized 500 ft. to accelerate to the free flow speed of the corridor. Based on this the region 500 ft. upstream and 500 ft. downstream of a given traffic control device was labeled accordingly (RDA for roundabout, AWS for all-way-stop, or TS for traffic signal). Figure 3.3 shows the route (green) with region of influence of respective traffic control devices highlighted in brown.

Table 3.2: Primary variables/parameters used in data analysis

Variable Names	Variables	Remark
NOx, HC, CO_2, CO and PM	Nitrogen oxides, hydrocarbons, carbon dioxide, carbon monoxide	Tail pipe emissions
RPM, Temp, MAP	Rotation per minute, intake air temperature, manifold absolute pressure	Give an idea of how much stress in put on the engine. It transforms to fuel demand.
Speed	Speed in miles per hour	
accl	acceleration = $\frac{d(\mathrm{Speed})/}{/dt}$ in mph/s	Isn't acceleration given by the PEMS? Why calculate it yourself?
jerk	jerk= $\frac{d(\mathrm{Accleration})}{dt}$	Indicator of driver aggressiveness
VSP	Vehicle specific power $= v * (1.1a + 0.132) + 0.000302 * v^3$ Where, v= speed in m/s and a= acceleration in m/s2	This variable is highly correlated with emissions (Jimenez-Palacios,1999)
gaspad	Positive acceleration = accl , if accl>0 =0, otherwise	Gas pedal use (indicator for acceleration behavior)
brakepad	negative acceleration =abs(accl) , if accl<0 =0, otherwise	brake pedal use (indicator for deceleration behavior)
DT	Date and time	
peakhour	Peak or off-peak hours	
TrafficD	Traffic devices (Roundabout, all-way-stop, Traffic signal) abbreviated as RDA, AWS, TS (or TS128)	
Driver	Denoted as D1, D2, D3 and D4	

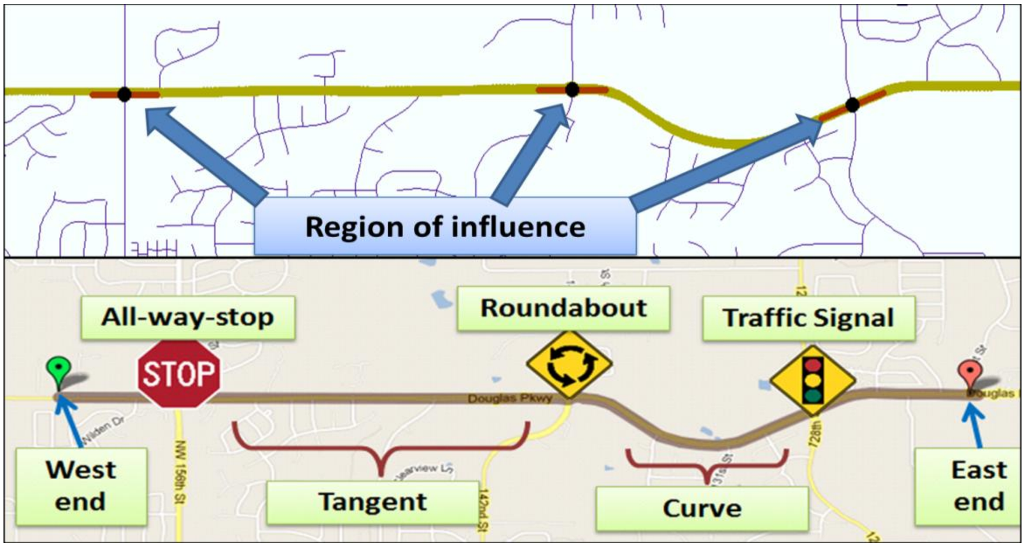

Figure 3.3: Route showing the region of influence (top figure) of the traffic control devices

For the purpose of data preparation, data manipulation, data analysis and reporting/post processing, more than 1000 lines of code were written in R (version 2.11.1). Excel 2007/2010 was used for data management. The following section describes the final datasets used for analysis.

3.5 Final dataset used for analysis

Data analysis was carried out using various driving behavior parameters. Table 3.2 shows primary driving behavior parameters (also called primary parameters). The divers drove for a total of 16 hours. This comprised of 38,000 observations of primary parameters. The secondary driving behavior parameters (also called secondary parameters) as shown in Table 3.3 were obtained by summarizing primary parameters and their combinations over trip-parts (region of influence of traffic control devices). These parameters were used by many researchers for characterizing driving cycles (Tong and Hung, 2010; Barlow et al., 2009). For a given trip, a driver encountered each traffic control device (roundabout, all-way-stop and traffic signal) on single occasion. Therefore, in 109 trips, 327 (3 x 109) trip-parts were recorded. The number of rows of secondary parameters was 327.

Table 3.3: Trip-part summarized variables

Driving behavior	Definition (units)		Relevance
v_min	minimum speed for the whole trip (mph)		Speed behavior
v_avg	average speed (mph)		
vrun_avg	average running speed (excluding observations with idling operation) (mph)		
v_max	maximum speed (mph)		
RMSs	root mean square speed (mph/s)	$\sum_{k=1}^{N}\sqrt{((speed_k^2)/N)}$ N is the number of seconds of data	
a_avg	average acceleration (mph/s)		Speed change behavior
d_avg	average deceleration (mph/s)		
j_avg	average jerk (mph/s)		
RMSa	root mean square acceleration (mph/s)	$\sum_{k=1}^{N}\sqrt{((accl_k^2)/N)}$	
ADS	Number of acceleration/deceleration shifts (number of speed changes)	$\sum_{k=1}^{N}\begin{cases}1, & if\ accl\ \geq 0.1 \text{ or } accl\ \leq -0.1\\ & 0, \text{otherwise}\end{cases}$ accl in $\mathrm{m/s2}$	
RPA	relative positive acceleration (mph/s)	$\frac{1}{distance}\sum_{k=1}^{N}\begin{cases}acccl\ x\ speed, & if\ accl > 0\\ & 0, \text{otherwise}\end{cases}$	
trip_len	trip length (s)	Duration of trip	Time spent in each mode
Pi	percent of time in idling mode (%)	Percentage of time when speed =0	
Pa	percent of time in accelerating mode (%)	Percentage of time when acceleration ≥ 0.1 m/s^2	
Pc	percent of time in cruise mode (%)	Percentage of time when speed < 5 m/s and -0.1 m/s^2 < acceleration < 0.1 m/s^2	
Pd	percent of time in decelerating mode (%)	Percentage of time when speed < 5 m/s and -0.1 m/s^2 < acceleration < 0.1 m/s^2	
PKE	positive kinetic energy (mph/s)	$\mathrm{PKE} = \frac{v_f^2 - v_i^2}{x}, \quad \frac{dv}{dt} > 0,$ Where v_f and v_i are the final and initial speeds, respectively, in an individual acceleration phase and x is the total travel distance	Energy gained or utilized
VSP_avg	Average value for vehicle specific power (m^2/s^2)		

Data analysis was carried out at three levels namely parameter level, trip-part level and micro-scale (second-by-second) level. Dataset corresponding to each level was described as follows. Table 3.4 shows summary of the analysis.

1.) **Exploring individual parameters**: In this case, distributions of driving behavior parameters were explored to compare driving behaviors across drivers and the traffic control devices. For analysis pertaining to drivers, primary parameters were used whereas for analysis on traffic control devices, both primary and secondary parameters were used. Detailed analysis is documented in Chapter-4.

2.) **Comparing traffic control devices:** In this analysis, driving behavior at roundabout was compared with that of all-way-stop and traffic control devices. In this case, secondary parameters used for conducting MANOVA with traffic control device as explanatory variable. Chapter -5 gives the details of this analysis.

3.) **Second-by-second data:** Second-by-second speed data at roundabout was used for analysis. The speed profiles of drivers at the roundabout were modeled using hierarchical Bayesian regression. The complete analysis is presented in Chaper-6.

Table 3.4: Summary of analysis done in future chapter

Analysis level	Data	Driving behavior parameters	Objective	Analysis
Parameter level	All observations	Speed, acceleration, VSP, gaspad, brakepad	Understanding parameters that quantify driving behavior	Exploring the frequency distributions of driving behavior parameters
Trip-part level	Driving behavior parameters summarized at each traffic control devices	Parameters derived primarily from speed, and acceleration (These parameters are used for defining standard driving cycles)	Comparing driving behavior at different traffic control devices	Performing MANOVA
Second-by-second level	Second by second speed profiles of each driver	Speed profile at the roundabout	Comparing driving behavior among drivers	Developing Hierarchical Bayesian regression model

CHAPTER 4. Study of Driving Parameters

4.1 Background and objectives:

The main objective of this dissertation is to study emissions in the light of driving behavior and traffic control devices. Previous researchers have identified various parameters that can quantify driving behavior at different levels. In this regard, this chapter explores few of these driving parameters to quantify and contrast driving behavior across individual drivers and across traffic control devices.

4.2 Data used in this analysis

In this chapter, exploration was done to explore if direction of travel and time of the day had any influence on driving behavior. Then, driving behavior was studied across drivers through speed (mph), acceleration (mph/s), VSP (W/kg), and jerk (mph/s^2). In addition, explored two new parameters gaspad (mph/s) and brakepad (mph/s) were also explored to assess how well they can explain variability in driving behavior.

Driving behavior across the three traffic control devices (roundabout, all-way-stop and traffic signal) was studied instantaneous speed, acceleration, “gaspad” and, “brakepad”. These variables represented instantaneous driving behavior. Additionally, we studied driving behavior in terms of positive kinetic energy (PKE), number of acceleration/deceleration shifts (ADS), relative positive acceleration (RPA), and VSP (m^2/s^2) where each one was aggregated over the area of influence of the respective traffic control device. These variables represented aggregate driving behavior. In this chapter, we based our conclusions on observations; no statistical tests were performed.

4.3 Observatory study

Apart from the vehicle type, driving behavior is likely to differ by traffic volume (correlated by time of the day), road geometry, individual driving habits and traffic control devices (roundabout, all-way-stop, traffic signals, curves and tangents). The following sections describes each of the above four characteristics that impacts driving behavior.

4.3.1 Time of the day and direction of travel

In this study, we collected data for both peak (7am to 9am and 5pm to7pm) and off-peak (9am to 11am and 3pm to 5pm) hours. Driving behavior quantified as speed, VSP, "gaspad" and "brakepad" was comparable between peak and off-peak hours (Figure 4.1). This may be because of low volumes or similar volumes in both the time periods. Ericsson (2000) found that difference in emission levels between peak and off-peak hours were not significantly different for less congested roads.

Similarly, driving behavior was comparable between both the directions of approach (Figure 4.2). This may like be due to similar road characteristic in both directions. This was also observed by the data collector who noted the queue positions at the intersections and in most cases the vehicle was at the beginning of the queue. This supported combining data in both directions. East bound trips were not distinguished from west bound trip in future chapters. The small differences seen in the graphs (Figure 4.1 - 4.2) were not significant.

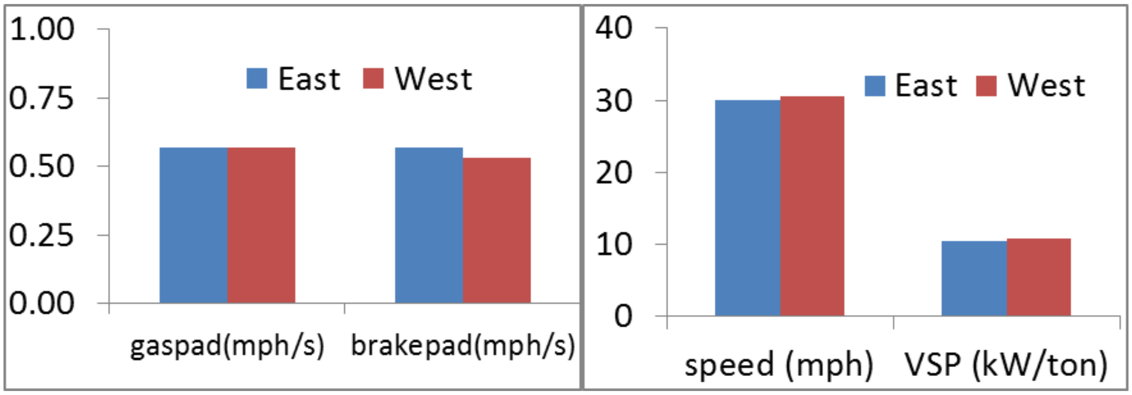

Figure 4.1: Driving behavior variable for peak and off-peak hours

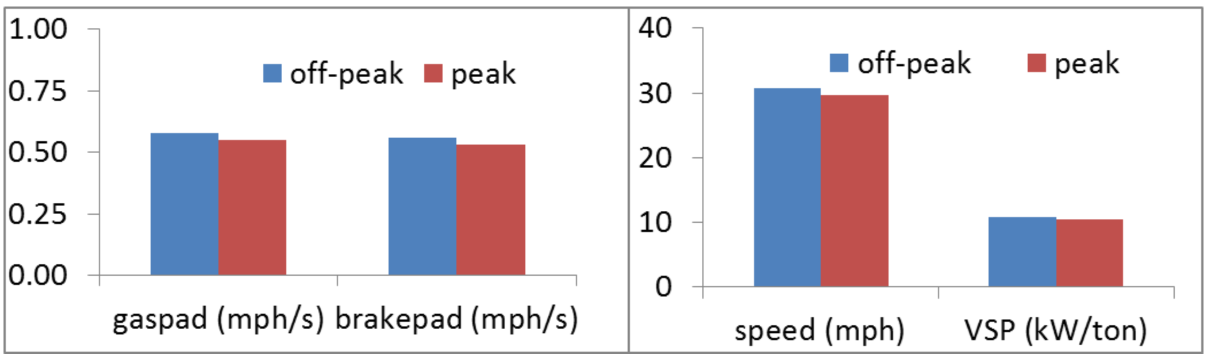

Figure 4.2: Driving behavior variable for east and west bound driving

Since driving behavior for different time of the day and direction of travel was not considerably different, we combined the data and performed an observatory analysis of driving across drivers and traffic control devices. The analyses are shown in the following sections.

4.3.2 Driving behavior by drivers

We analyzed driving behavior with respect to drivers using selected driving parameters. Instead of average values, we studied the distributions of each driving parameters. The following observations were made.

1.) Speed was uniform across drivers, which implied that the drivers maintained similar speeds overall. However, in order to make concrete conclusions, it is important to consider other parameters that characterize driving behavior. Driver-3 (D3) seemed to have pushed the gas pedal less often as compared to other drivers as depicted by frequency of zero acceleration in. Lower emissions are expected in this case.

2.) Driver-1 and Driver-3 demonstrated VSP of 20 W/kg or higher on more occasions than the other drivers (Figure 4.5). This implied that Driver-1 and Driver-3 utilized higher power from the engine as compared to the other drivers. Also, VSP has been shown to explain large variability in emissions. Driver-1 and Driver-3 are expected to generate higher emissions since VSP is highly correlated to emissions (Jimenez-Palacios, 1999). This is supported by CO2 emissions corresponding to each driver (Figure 4.6). Driver-2 and Driver-4 exhibited similar driving behavior as shown by most parameters. Likewise, Driver-1 and Driver-3 drove displayed similarly driving behavior as depicted by acceleration, VSP, gaspad, brakepad and jerk (Figure 4.4 to Figure 4.9). The parameters namely “gaspad” and “brakepad” were also similar for the above two driver pairs (Figure 4.7). This implied that gaspad and brakepad can be used as driving behavior parameters.

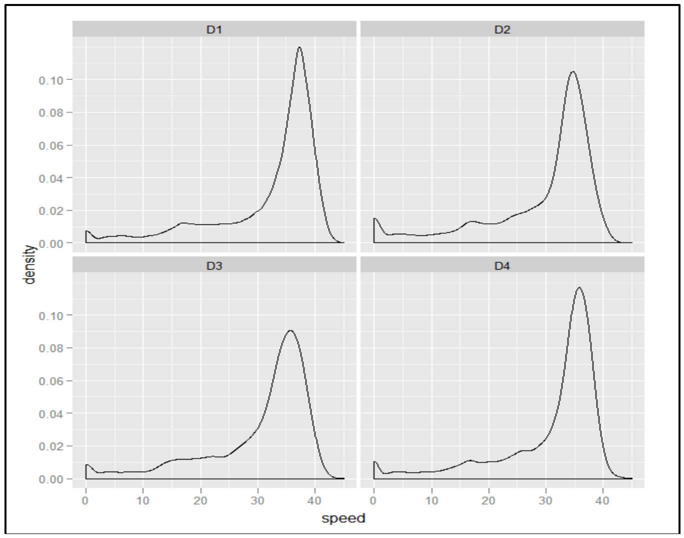

Figure 4.3: Distribution of speed by drivers

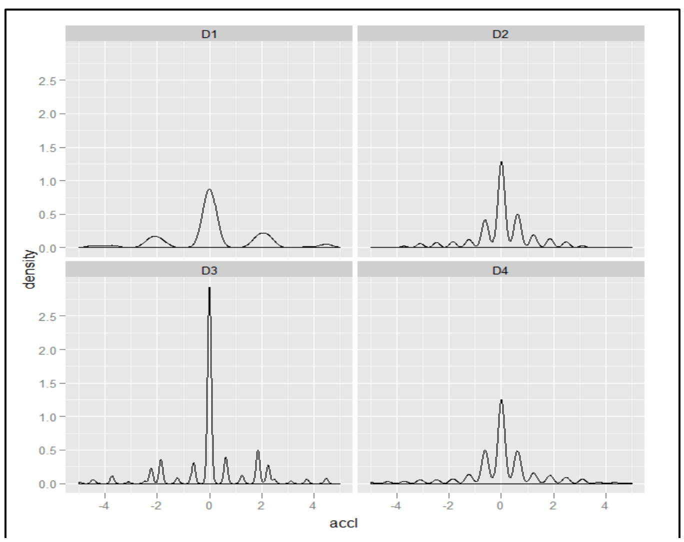

Figure 4.4: Distribution of acceleration by drivers

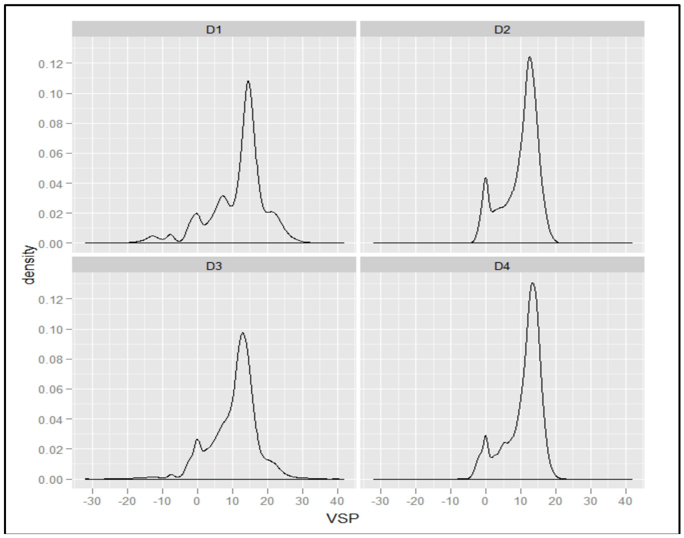

Figure 4.5: Distribution of VSP by drivers

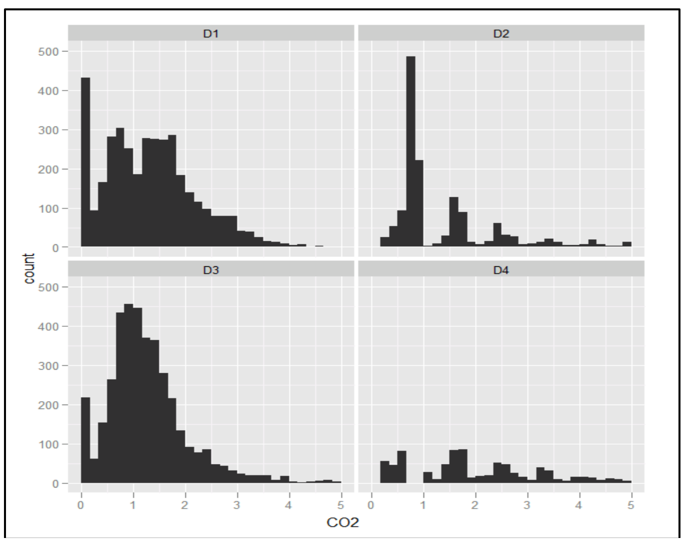

Figure 4.6: Distribution of CO_2 by drivers

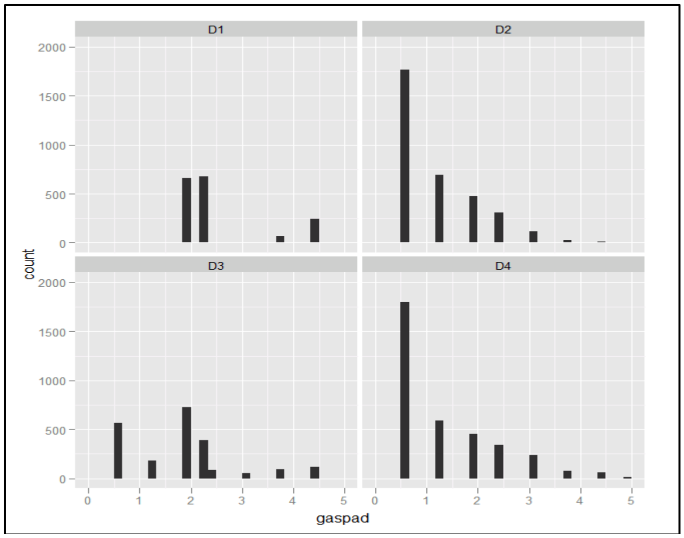

Figure 4.7: Histogram of gaspad by drivers

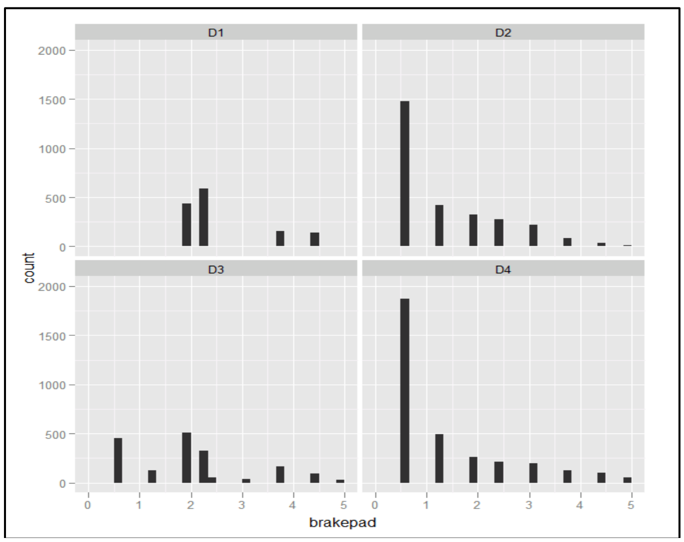

Figure 4.8: Histogram of brakepad by drivers

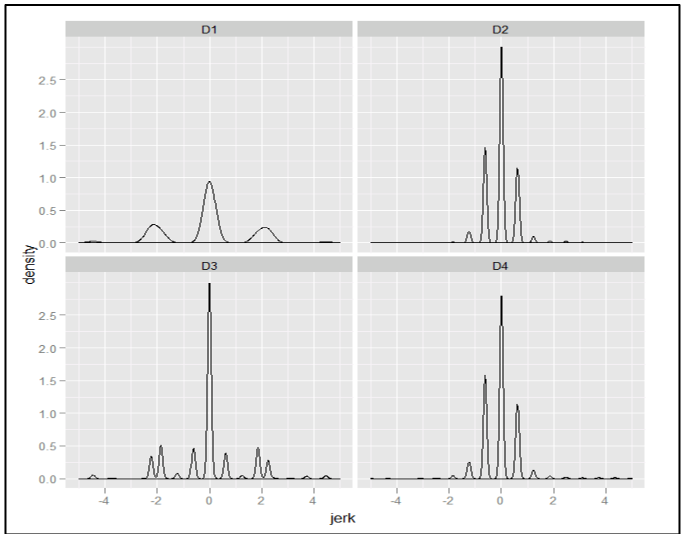

Figure 4.9: Distribution of jerk by drivers

The exploratory study done in this section was helpful in understanding the impact of individual driving parameters on emissions. In the following section, driving behavior is studied in terms of various traffic control devices.

4.3.3 Driving behavior by traffic control devices

In this section, driving behaviors were assessed at different traffic control devices. Apart from vehicle kinematics (speed, acceleration and VSP), other parameters were derived for quantifying certain driving behaviors. These include ADS (acceleration-deceleration shifts), RPA (relative positive acceleration) and PKE (positive kinetic energy) as discussed earlier. The following results were obtained:

1.) Acceleration, “gaspad”, and “brakepad” at roundabout and all-way-stop had similar distributions (Figure 4.10 to Figure 4.12). Emissions were expected to be comparable in case of roundabout and all-way-stop.

2.) Positive kinetic energy (PKE) was greatest for all-way-stop followed by traffic signal and roundabout (Figure 4.13). PKE depicts the aggressive driving behavior (André, 1996). Drivers were more aggressive at all-way-stop than at other traffic control devices.

3.) Acceleration-deceleration shifts for all-way-stop and roundabout were centered at the value of 30 and 25 respectively with small standard deviation (Figure 4.14). ADS for traffic signal have wider spread. This implied that driving behavior at traffic signal varied from trip to trip. This implies that emissions at traffic signal may be either lower of higher than roundabout and all-way-stop when compared across various trips.

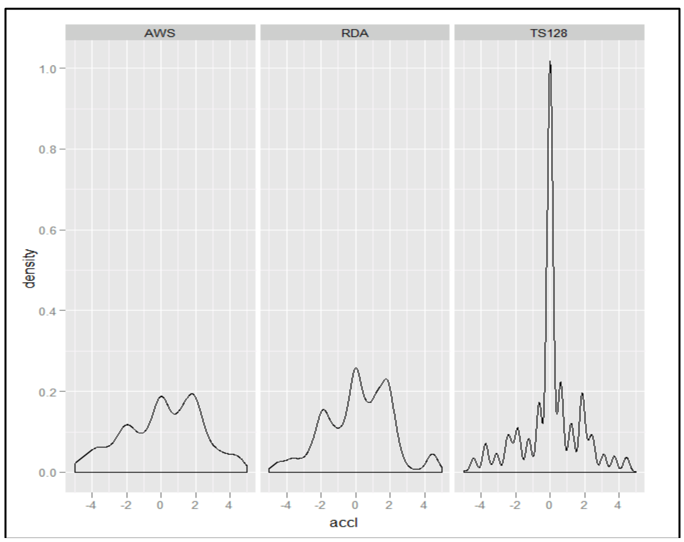

Figure 4.10: Distribution of acceleration by traffic control devices

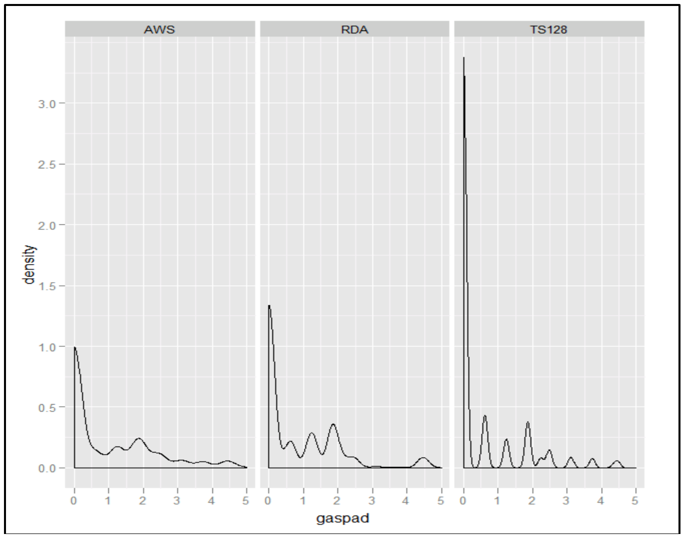

Figure 4.11: Distribution of gaspad by traffic control devices

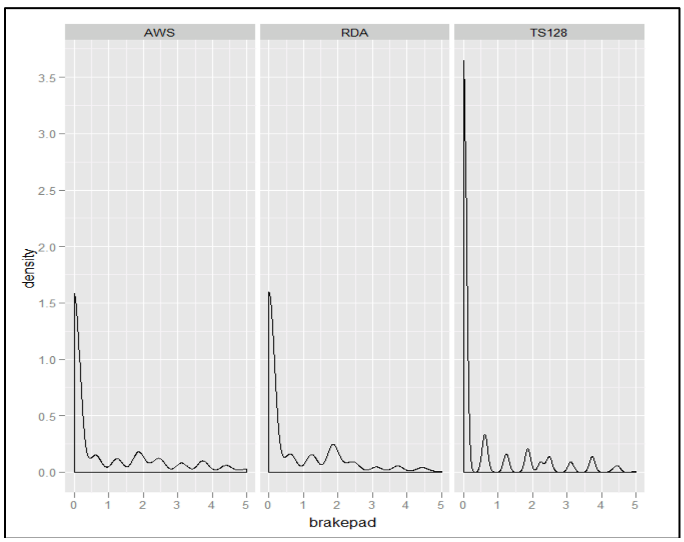

Figure 4.12: Distribution of brakepad by traffic control devices

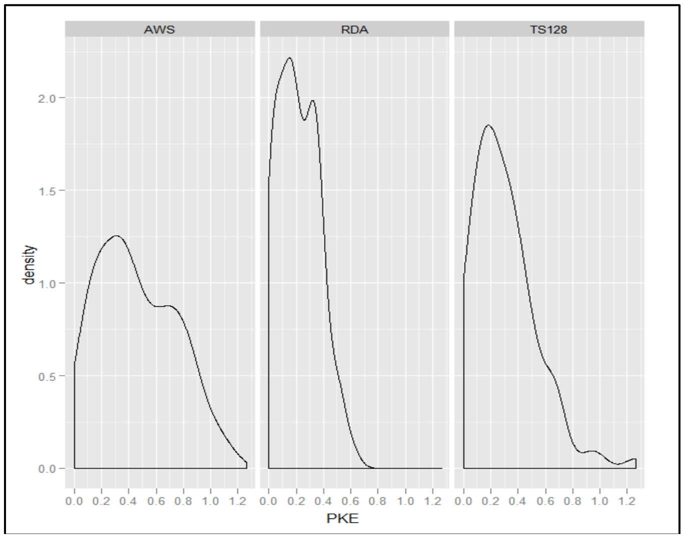

Figure 4.13: Distribution of positive kinetic energy (PKE) by traffic control devices

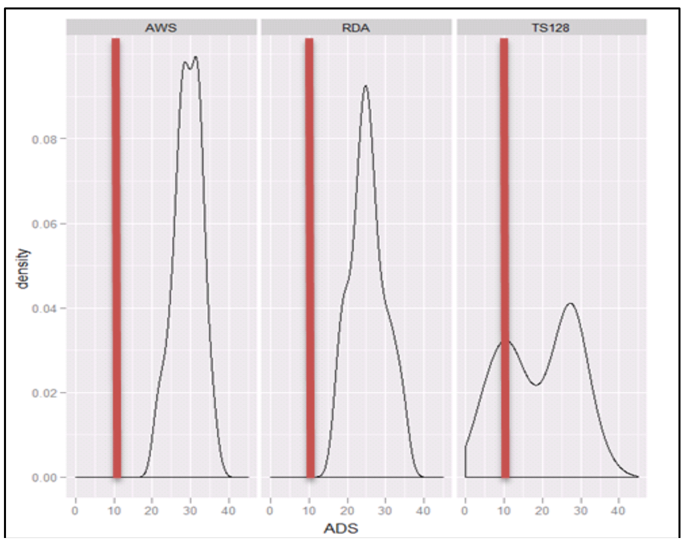

Figure 4.14: Distribution of ADS by traffic control devices

4.4 Summary

Driving behavior among driver was studied in terms of various kinematics variables which were useful in characterizing driving behavior of individual drivers and of a typical driver at various traffic control devices. Driving behavior parameters corroborated one another while explaining emissions characteristic.

Driving behavior parameters illustrated that Driver-1 and Driver-3 had similar driving behavior, while Driver-2 and Driver-4 drove similarly. Driving behavior parameters were helpful in studying specific driving behaviors. Emissions for Driver-1 and Driver-3 were similar. Same was the case with Driver-2 and Driver-4. These parameters can be used to classify driving behavior between individual drivers.

Exploratory study of driving behavior at various traffic control devices revealed that driving behaviors at roundabout and all-way-stop were comparable. Emissions are also expected to be comparable. This implies that replacing a roundabout with all-way-stop under the given conditions, would not likely to have significant environmental benefits.

The analysis done in this chapter was observational. In order to validate the assumptions and findings, standard statistical tests were performed. The following two chapters describe the analyses in detail.

CHAPTER 5. Comparison of Driving Behavior at Traffic Control Devices

5.1 Background and objectives

Vehicular emissions are highly correlated with driving behavior. Literature reviews showed that emissions at intersections are in general higher than those at the mid-blocks of the roads. This is related to the fact that at intersections, acceleration events are likely to occur with higher frequency. In most cases, driving through an intersection entails stopping or slowing down resulting in acceleration events which are associated with higher emissions (Rouphail et al., 2000). Previous researchers have compared emissions at roundabout, all-way-stop, and traffic signals (Ahn et al., 2009). However, they have not analyzed driving behavior at these traffic control devices.

The analysis conducted in the last chapter (Chapter 4) showed that driving behavior at all-way-stops and roundabouts were similar. Driving behavior and emissions at traffic signals were observed to be different from those at a roundabout and all-way-stop. This chapter examines driving behavior differs across traffic devices. To achieve this, driving behaviors between traffic devices were compared using a multivariate analysis of variance (MANOVA) model. In specific, the analysis described in this chapter attempts to answer the following questions:

1.) Is the driving behavior on a roundabout and a traffic signal significantly different?

2.) Is there any significant difference in driving behavior on a roundabout and an all-way-stop?

5.2 Data set used in this analysis

Originally, the data recorded by the PEMS consisted of second by second observations of speed, acceleration, engine parameters (engine rpm, engine intake temperature and manifold absolute pressure) and emissions. For each one second observation, VSP was computed from speed and acceleration assuming the road grade to be negligible. For light duty vehicles, VSP is given by the following equation:

$VSP = v*(1.1a+0.132) +0.000302*v^3$, where v is speed (m/s) and a is acceleration (m/s^2).

Every observation corresponding to a traffic control device was obtained by summarizing each parameter over a specific trip-part through the device. Data for a given trip and device were reduced to one observation. The result was many such summarized observations for each traffic control device (Figure 5.1). The region of influence of the traffic control devices was defined as 500 ft. downstream to 500ft. upstream of the center of the road intersection. The parameters, defined in Table 5.1, were RMSs, RMSa, ADS, RPA, PKE, and VSP_avg (average VSP over the region of influence of traffic control devices). Past research has used these parameters in constructing and evaluating driving cycles (Tong and Hung, 2010). Table 5.1 describes these variables in detail. Driving behavior parameters were found to be correlated and this justified the use of a multivariate model – MANOVA for comparing driving behavior between pairs of traffic control devices. Drivers were chosen randomly from the population and in order to incorporate the individual driving characteristic, the variable “Driver” was included in the model. The following section describes the theoretical framework of the MANOVA model.

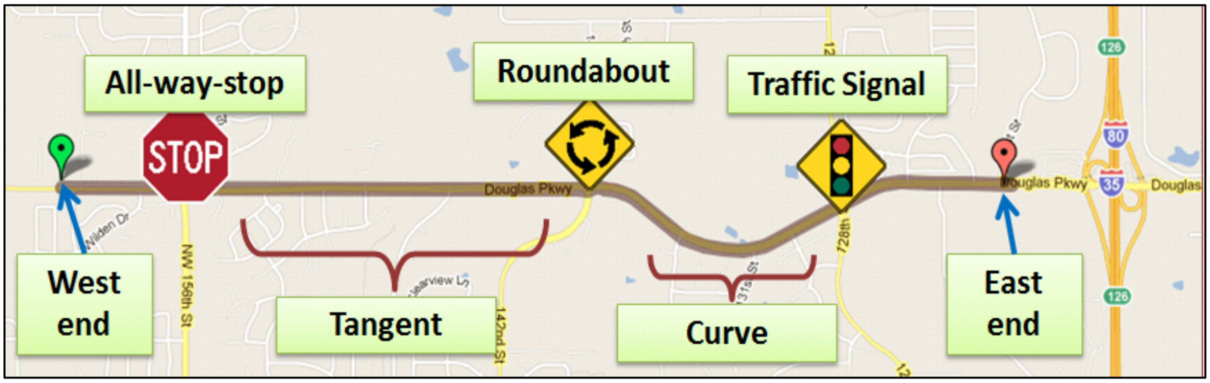

Figure 5.1: The study route (gray color) showing the various traffic devices.

Table 5.1: Driver behavior parameters (Parameters used for characterizing driving behavior)

Driving behavior parameter	Definition	Units	Relevance
RMSs	Root mean square speed	mph/s	Speed behavior
RMSa	Root mean square acceleration	mph/s	Speed change behavior
ADS	Number of acceleration/deceleration shifts (number of speed changes)	a number	
RPA	Relative positive acceleration This is proportional to average acceleration power of a vehicle	mph/s	
PKE	Positive kinetic energy	mph/s	Energy gained by vehicle and utilized by the engine
VSP_avg	Average value for vehicle specific power	m^2/s^2	

5.3 MANOVA

MANOVA is an extension of analysis of variance (ANOVA) model in which dependent variables are evaluated on a combination of dependent variables. It is used for comparing the means of several groups with many variables. The MANOVA model for g groups is given by

$Y_{lj} = \mu_l + e_{lj} = \mu + \tau_l + e_{lj}, j = 1,2 \dots n_l$ and $l = 1,2,3 \dots g$,where, Y is the dependent variable. The null hypothesis for the MANOVA model with g groups (or population) can be written as

$H_0: \mu_1 = \mu_2 = \mu_3 = \cdots = \mu_g$

where, $\mu_l = \mu + \tau_l$ (μ_l is the l^{th} group mean vector)

l^{th} Population mean = overall mean + l^{th} population

The alternative hypothesis H_a is that at least one of $\tau_l \neq 0$. The assumptions required in using MANOVA are as follows:

1) The random samples from different populations are different.
2) All populations have a common covariance matrix Σ.
3) Each group is multivariate normal

The test statistic used for testing the null hypothesis of a MANOVA model is Wilk's lambda (Λ) given by $\Lambda = \frac{W}{B+T}$, where, W is the within sum of square error and B is between (groups) sum of the square error. Λ is used as a statistic to test if there is any difference between the means of the given groups on a combination of dependent variables. In multivariate analysis, Λ plays the same role as F-test does in one-way ANOVA. It measures the proportion of variance across groups in terms of a combination of variables.

If Λ is small, the null hypothesis is rejected concluding that the mean (dependent variable) of at least one of the variable in the groups is significantly different. Distribution of Λ is not straightforward but can be approximated as shown in Table 5.2. For large sample sizes, a modification of Λ due to Bartlett is used for testing H_o (Johnson and Wichern, 2007). P-value for the tests can be obtained from the approximated distribution.

Table 5.2: Distribution of Wilks' lambda, Λ (Taken from Johnson and Wichern (2007))

No. of variables	No. of groups	Sampling distribution for multivariate normal data
$p = 1$	$g \geq 2$	$\left(\frac{\Sigma n_\ell - g}{g - 1}\right)\left(\frac{1 - \Lambda^*}{\Lambda^*}\right) \sim F_{g-1, \Sigma n_\ell - g}$
$p = 2$	$g \geq 2$	$\left(\frac{\Sigma n_\ell - g - 1}{g - 1}\right)\left(\frac{1 - \sqrt{\Lambda^*}}{\sqrt{\Lambda^*}}\right) \sim F_{2(g-1), 2(\Sigma n_\ell - g - 1)}$
$p \geq 1$	$g = 2$	$\left(\frac{\Sigma n_\ell - p - 1}{p}\right)\left(\frac{1 - \Lambda^*}{\Lambda^*}\right) \sim F_{p, \Sigma n_\ell - p - 1}$
$p \geq 1$	$g = 3$	$\left(\frac{\Sigma n_\ell - p - 2}{p}\right)\left(\frac{1 - \sqrt{\Lambda^*}}{\sqrt{\Lambda^*}}\right) \sim F_{2p, 2(\Sigma n_\ell - p - 2)}$

The next section presents the model setup and assumption for the specific MANOVA models estimated in this chapter.

5.4 Model outline and assumptions

In this study, an attempt was made to compare driving behavior between traffic control devices. Driving behavior (DB) was a vector comprising of driving behavior parameters (Table 5.1) with dimension of seven (RMSs, RMSa, ADS, RPA, PKE and VSP_avg, and Driver). "Driver" was a qualitative variable. The vector DB associated with each traffic control device has a dimension of RxM, where R is number of observations and M (=7) is the number of response variables (driving behavior parameters). The mean DB vector (averaged over the region of corresponding traffic control devices) for i^{th} traffic control device is given by μ_i and is a vector of dimension [Mx1].

DB = (RMSs, RMSa, ADS, RPA, PKE, VSP_avg, Driver) is distributed as N (μ_lβ, Σ), where β is an unknown matrix of regression coefficients of dimension [RxM] and Σ is a [RxM]x[RxM] matrix with a diagonal block structure $\Sigma = \text{diag}\{\Sigma_i\}$, where each block is a [MxM] matrix. The null hypothesis of equality of mean is given by

H_0: $\mu_{\text{traffic device1}} = \mu_{\text{traffic device2}}$ with respect to the alternative hypothesis

H_a: $\mu_{\text{traffic device1}} \neq \mu_{\text{traffic device2}}$

The MANOVA model can be stated as: DB ~ μ +TD +error. The justifications for assumptions made in the MANOVA model are as follows:

1) The speed profile of a given driver at a given traffic device was similar across runs. However, trip summarized values of the driving behavior parameters were assumed to be independent.

2) Covariance matrix Σ corresponding to different traffic can be reasonably assumed to be similar.

3) The distributions of driving behavior parameters were bell shaped. The vector comprising these parameters was assumed to have a multivariate distribution.

The data management and analysis was done using Excel (2010) and R (version 2.11.1). Wilks's lambda for the overall difference in means of driving behavior vector of different traffic device was computed. Significance of each driving behavior parameter was also reported. This was done to explore which driving behavior parameter(s) in particular was (were) responsible for the significant difference in mean. The following section presents the results of two MANOVA models. The p-values for the difference in individual driving behavior parameters were obtained from the F-statistics of ANOVA.

5.5 Results and discussion

The analysis addressed two questions as stated in section 5.1. In this regard, two MANOVA models were estimated for comparing driving behavior between (1) traffic signal and roundabout, and between (2) all-way-stop and roundabout. The model examines if the difference is due to random chance or inherent characteristic of driving at the two traffic control devices.

5.5.1 Driving behavior comparison: traffic signal and roundabout

The traffic signals and the roundabouts have their respective advantages. While vehicles on a roundabout were found to produce lower emissions on local roads (Mandavilli et al., 2003), a traffic signal was found to be environmentally friendly for high volume roads (Ahn et al., 2009). Emissions at the two traffic control devices basically depend on the traffic volume, and driver behavior. In this dissertation, the chosen traffic corridor (Douglas Avenue, Urbandale, IA) has low to moderate volume.

This section presents the result on comparison of driving behavior manifested by a typical driver at traffic signal as compared to a roundabout. The study attempted to answer the question whether the difference in driving behavior at traffic signal and roundabout is because of random chance or not. In this regard, the following null hypothesis was tested at 5% significance level. H_0: $\mu_{traffic\ signal} = \mu_{roundabout}$ versus H_a: $\mu_{traffic\ signal} \neq \mu_{roundabout}$

Where, $\mu_{traffic\ signal}$ and $\mu_{roundabout}$ are the estimates for the mean driving behavior vector (DB) at the traffic signal and the roundabout, respectively. The number of observations (R) for roundabout and traffic signal was 216.

The results, shown in Table 3, suggest that there was significant difference in driving behavior at the two traffic devices. Wilks' lamba for the test was 0.35 with p-value less than 0.001. Specifically, RMSs, ADS, PKE and VSP_avg were significantly different. The RMSs or operation speed for roundabout was lower as compared to traffic signal.

In case of a traffic signal, a driver is not sure in advance if he/she would need to stop at the traffic signal. This increases the tendency for hard acceleration which is a characteristic of aggressive driving. This was validated by the fact that, positive kinetic energy and average VSP at the traffic signal was higher. Since, emissions are highly correlated with VSP, driving at the traffic signal would lead to higher emissions.

Driving behavior parameters taken on aggregate level showed that driving behavior at roundabout and all-way-stop was comparable. In order to validate this, statistical tests were performed as stated in this chapter. Driving behavior at the all-way-stop and the roundabout was evaluated on the basis of the following null hypothesis tested at 5% significance level.

H_0: $\mu_{all\text{-}way\text{-}stop} = \mu_{roundabout}$ versus H_a: $\mu_{all\text{-}way\text{-}stop} \neq \mu_{roundabout}$

The number of observations for both the traffic devices together was 215. Result showed that there was significant difference in driving behavior at an all-way-stop and roundabout. Wilks' lamba for the test was 0.66 (p-value < 0.001).

5.5.2 Driving behavior comparison: all-way-stop and roundabout

All numeric parameters were significantly between roundabout and traffic signal. However, in this case also, the drivers did not have significantly different characteristics. The operation speed (RMSs) at roundabout was significantly higher than that at the all-way-stop.

Aggressiveness as measured by the speed change tendency (ADS, RMSa, RPA) was higher for all-way-stop as compared to roundabout. Energy gained parameter showed mixed result with both being significantly different between the two traffic control devices under consideration.

Table 5.3: Difference in means of driving behavior parameters (traffic signal and roundabout)

Driving behavior parameters	Mean driving behavior vector for Roundabout	Mean driving behavior vector for Traffic signal	p-values (difference in means)	Relevance
RMSs	24.73	27.64	3.05e-05	Operation speed behavior
ADS	25.31	19.90	2.45e-07	Speed change tendency
RMSa	2.42	1.98	0.093	
RPA	1.01	0.84	0.080	
PKE	0.21	0.29	0.003	Energy gained
VSP_avg	6.50	8.70	9.95e-08	
Driver			0.990	Individual driver characteristcs

5.6 Summary

The driving behavior parameters were correlated and therefore MANOVA was performed to compare aggregate measures of driving behavior across traffic devices. It was found that driving behavior at a roundabout was significantly different from that at a traffic signal and an all-way-stop.

Table 5.4: Difference in means of driving behavior parameters (all-way-stop and roundabout)

Driving behavior parameters	Mean driving behavior vector for roundabout	Mean driving behavior vector for all-way-stop	p-values (difference in means)	Relevance
RMSs	24.73	22.82	9.03e-16	Operation speed behavior
ADS	25.31	29.22	5.75e-11	Speed change tendency
RMSa	2.42	3.31	7.20e-4	
RPA	1.01	1.25	0.039	
PKE	0.21	0.45	1.55e-12	Energy gained
VSP_avg	6.5	5.76	9.01e-08	
Driver			0.92	Individual driver characteristcs

The above analysis showed that driving behavior at a given traffic device was not unique. This implies that traffic devices should be treated separately in modeling emissions and fuel consumption. This is useful in developing emissions factors taking the traffic device into consideration in addition to individual vehicle types as it is done at present. Findings presented in this chapter must be verified with measured emissions data.

Drivers were not significantly different when observations were aggregated. Driving behavior at higher resolutions must be studied in order to find potential emission hotspots on road sections or traffic control devices. In the next chapter, driving behavior of individual drivers would be modeled on one second resolution to find important instantaneous driving behaviors.

CHAPTER 6. A Hierarchical Bayesian Model for Driving Behavior at a Roundabout

6.1 Background and objectives

In Chapter four, driving behavior across drivers was explored using distributions of driving behavior parameters. Not all drivers drove similarly. The analysis was had two limitations. First, it was exploratory. Second, it did not provide understanding of the instantaneous driving behavior. Ignoring the instantaneous variation in individual profile easily leads to aggregation bias (Laureshyn et al., 2009). Therefore, there was a need for a model which can be used for comparing second-by-second driving characteristic/behavior.

The objective of this chapter was to assess if driving behavior at intersections was similar enough to be represented by single model for all drivers. This objective was achieved through modeling and comparing second-by-second driving behavior across drivers as described in this chapter. As noted in Chapter 3, vehicle activity data were collected at roundabout, all-way-stop, and traffic signal on Douglas Avenue (Urbandale, IA). However, due to limited resources, only driving behavior at roundabouts was modeled because of the following advantages.

1.) Modeling the whole trip would require significant assumptions and complicated statistical methods which are beyond the scope of this dissertation.

2.) A roundabout is a traffic device whence all the four primary modes of vehicle operation namely idling, cruise, acceleration and deceleration are present in almost all the trips. A vehicle driven through a roundabout must slow down (deceleration), cruise along (cruise) or stop (idling), and finally accelerate (acceleration) to attain the flow speed. Therefore, a driver on a roundabout is more likely to exhibit most driving modes present in a typical trip.

3.) As shown in Chapter-4, the “acceleration-deceleration shift” parameter for the roundabout was centered on 25 with small standard deviation thereby indicating similar driving behavior across trips. Driving behavior at signalized intersection is highly dependent on signal state so each trip by a driver through a signalized intersection may have a completely different driving trace.

Speed is an important parameter that can quantify driving behavior (Ericsson, 2000). The most common driving behavior parameters are derived from speed (Jimenez-Palacios, 1999). In this chapter, an attempt was made to use speed, a driving behavior parameter, for modeling driving behavior of different drivers at the roundabout using Bayesian hierarchical regression model. The following section deals with Bayesian philosophy and Bayesian hierarchical inference method. Next, the data used in the model is discussed followed by the model framework, results and discussion. Finally, the summary of findings and conclusions are presented.

6.1.1 Bayesian philosophy

Bayesian inference is primarily based on Bayes theorem which is a method of keeping track of uncertainty. Bayes theorem provides a method by which subsequent probability/belief about an event/parameter is updated with observed data. The updated probability is estimated by conditioning the prior (prior to observation) probability on the observed data.

In a Bayesian approach, firstly a model is formulated as is done in case of classical statistics. This is followed by assuming a probability distribution (called prior distribution) for the unknown parameters in the model. This is called prior since it is not based on data but some kind of subjective reasoning before utilizing the information in the observed data. The probability distribution of the parameters is updated based on the available data and Bayes's rule. This updated probability distribution is called posterior distribution which is believed to encompass data as well as the prior believe and therefore serves as a model for the parameters. Summary of important contrasts between Bayesian and frequentist methods are presented in Table 6.1.

6.1.2 Markov chain Monte Carlo (MCMC)

Marcov chain is a type of process where outcome of an event at a given stage is only dependent on the outcome of the event at the previous stage (Greenshield and Shell, 2006).

Given a complex integral $\int_a^b h(x)dx$, if we can find a function *f(x)* and probability density *p(x)* defined over the interval (a,b) such that

$$\int_a^b h(x)dx = \int_a^b f(x)p(x)dx = E_{p(x)}[f(x)]$$

Table 6.1: Summary of key differences between the two methods
(Source: O'Hagan and Luce, 2003)

FREQUENTIST	BAYESIAN
Nature of probability	
Probability is a limiting, long-run frequency	Probability measures a personal degree of belief
It only applies to events that are (at least in principle) repeatable	It applies to any event or proposition about which we are uncertain
Nature of parameters	
Parameters are not repeatable or random	Parameters are unknown
They are therefore not random variables, but fixed (unknown) quantities	They are therefore random variables
Nature of inference	
Does not (although it appears to) make statements about parameters	Makes direct probability statements about parameters
Interpreted in terms of long-run repetition	Interpreted in terms of evidence from the observed data
Example	
"We reject this hypothesis at the 5% level of significance"	"The probability that this hypothesis is true is 0.05"
In 5% of samples where the hypothesis is true it will be rejected (but nothing is stated about the sample)	The statement applies on the basis of *this* sample (as a degree of belief)

For a large number of random draws x_i from $p(x)$, $\int_a^b h(x)dx$ can be approximated by

$$\int_a^b h(x)dx = E_{p(x)}[f(x)] \approx \frac{1}{n}\sum_{i=1}^{n} f(x_i)$$

This method of integration based on the above approximation is called Monte Carlo integration. It has made the computation of marginal distributions faster and easier (Walsh, 2004). The MCMC technique used in Bayesian inference is a simulation technique that is used for drawing a large sample from any distribution. Gibbs sampler is a type of MCMC method that provides an alternative for approximating marginal distribution $f(x)$ which is traditionally obtained by integrating the joint probability density function as

$$f(x) = \int \dots \int f\left(x, y_1, y_2, \dots, y_p\right) dy_1 dy_2 \dots dy_{p,}$$

There are many situations where this integration is not straight forward and almost impossible to perform even through numerical approximations (Casella and George, 1992). However, a large sized random sample from an approximate distribution is likely to generate samples from the exact distribution. Desired statistics pertaining to the exact distribution can be computed from this so called inferential sample (approximated distribution) to a great accuracy (O'Hagan and Luce, 2003).

6.1.3 Bayesian hierarchical inference

A hierarchical problem involves a population with a hierarchical or multilevel structure. Such a population is composed of many sub-populations. Observations in each sub-population are correlated and therefore standard statistical tests do not apply. Bayesian hierarchical models (also known as multilevel models) are used when information is contributed by various different levels of variability (Gelman et al., 2004). In general, all Bayesian models are hierarchical models. However, when the level of hierarchy becomes more than two, they are especially called Bayesian hierarchical models. The three levels in the model can be stated as

1) Data model: $y|\ x,\theta_y$

2) Process model: $x|\ \theta_x$

3) Parameter model: θ_x , θ_y

The Hierarchical Bayesian framework was chosen for this analysis for the following reasons.

1.) It takes better account of uncertainties in models and parameters and provides robust estimations of parameters.
2.) It provides individual-level models and permits estimation of models which are too demanding for traditional methods.
3.) It provides confidential interval for relevant non-linear parameters

The next section describes the data used in the hierarchical Bayesian regression model.

6.2 Data set used in this analysis

On the study route, the PEMS recorded speed and spatial location (latitude, longitude) on a second-by-second basis. The method chosen in the study was to fit speed profiles at the roundabout with a polynomial in position. Speed was plotted against spatial position (distance) along the route which was oriented in the east/west direction. The road geometry was different at the two approaches were data were collected (east bound and west bound) of the roundabout. Consequently, for consistency, only data from the east bound direction of travel was used for the analysis. The data chosen for developing the Bayesian hierarchical model consisted of speed profiles from 58 roundabout trip-parts for the eastbound direction of travel. Trip-part of a given traffic control device was defined (Chapter-3) as the vehicle traces within the region of influence of the associated traffic control device.

The GPS records data at one second intervals, as a result, the spatial location of data points differs from trip to trip as shown in Figure 6.1. As a result, it was necessary to normalize location between trips so that data could be compared.

In order to normalize distance, common points were identified for all trip-parts and position was extrapolated from the original GPS trace to the identified common point. A trajectory of 44 points (yellow points in

Figure 6.2) separated by 10 ft. was defined.

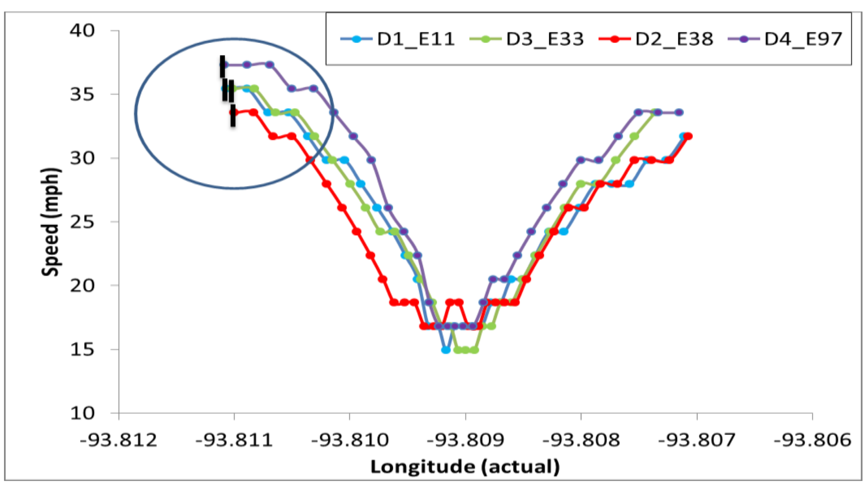

Figure 6.1: Speed profiles for few roundabout trip-parts made by different drivers (D1 to D4)

The gap was taken as 10 ft. since the vehicles travelled 40 ft. at an average every second and therefore consecutive observations were more than 10 ft. geographical distance. Moreover, these 44 points were sufficient to cover the area of influence of the roundabout. Speed for each trip-part was spatially interpolated at these 44 points. This resulted in speed profiles with common points, which were separated by a distance of 10 ft. (Figure 6.3).

Figure 6.2: Standard forty-four points chosen at the roundabout area of influence

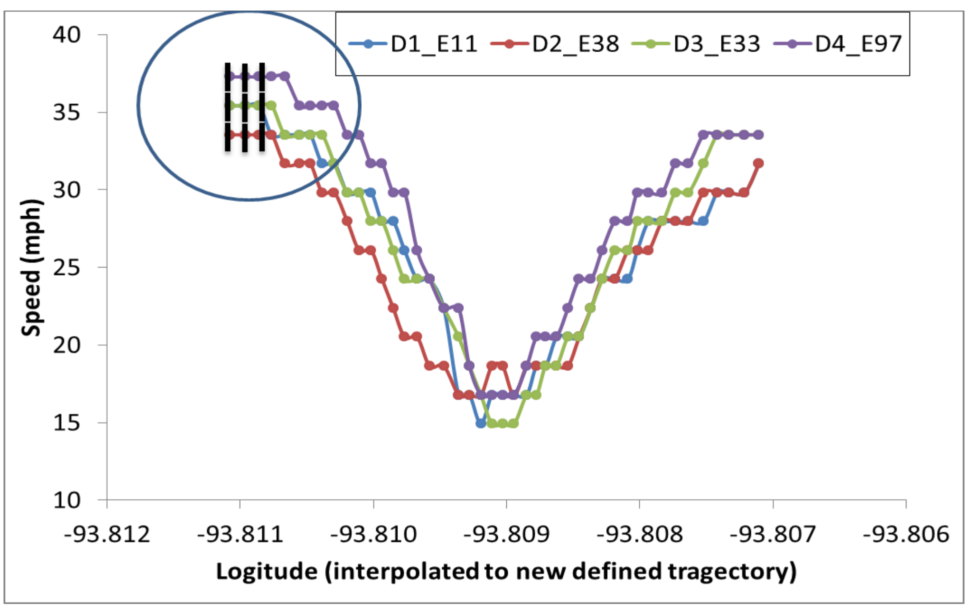

Figure 6.3: Interpolated speed profiles of some roundabout trip-parts

6.3 Speed profile modeling

On negligibly few trips the drivers completely stopped at the yield point of the roundabout to yield to circulating traffic. Speed profiles corresponding to these trips were not included in the model. This was done to eliminate driving behavior resulting from other vehicles in the roundabout.

It was assumed that the speed profiles for a given driver were correlated. For each driver, we obtained an average speed profile by averaging the speed profiles at each of the 44 longitude points. The individual average speed profiles were fitted with a 4^{th} degree polynomial in position (longitude) using the statistical language R (Version 2.11). The route runs from east-west direction, therefore, latitude was almost the same for the entire route. This made it sufficient to use on longitude as position variable.

A Bayesian hierarchical regression model for speed was developed for all drivers. Regression coefficients for each driver were assumed to be normally distributed. Conditional distributions (or conditionals) for each parameter were derived from the joint posterior distribution for all parameters/coefficients. Samples of these coefficients were drawn from their conditionals using Gibbs sampler. The step by step description of the model is given in the following section.

6.3.1 Model set up and assumptions

Bayesian Hierarchical model, a multi-level model was chosen for fitting the speed profiles with respect to the position. The mean speeds of drivers (μ_{Driver}) were level-one parameters. The coefficients of regression (β_{Driver}) equations of speed profile for each driver were level-two parameters. The means ($\mu_{\beta Driver}$) and variances ($\sigma_{\beta Driver}$) of the regression coefficients were the level-three parameters (Figure 6.4). These means and variances were assumed to have come from Normal and Inverse gamma distributions respectively.

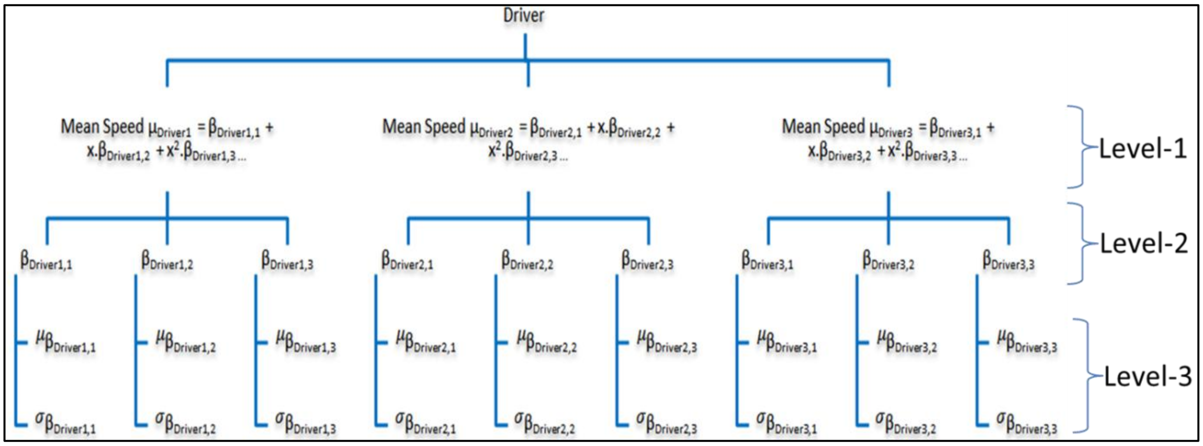

Figure 6.4: Flow chart of various levels of parameters in Bayesian Hierarchical model

Speed profiles were dependent on the relative position of the points with respect to the roundabout and therefore the actual values of longitude were not important. Without any loss of information, we replaced the independent variable (longitude) with its index, which was 1 to 44. Consequently, the independent variable for the model was x with values from 1 to 44. The above step was taken to simplify the calculation and analysis.

The speed profiles were modeled with a fourth degree polynomial in x (longitude). High correlations were expected among even as well as odd powers of x. This resulted in multicollinearity. Correlations among x, x^2, x^3, x^4 were minimized by setting x to (x-mean(x)). This transformation is also called centering.

Let y_{ij} denotes the mean speed for driver i at position index j, measured in mph. Let x_j denotes the dependent variable corresponding to position (longitude). Here, i = 1 to N, j=1 to J, where N=4, J=44. The regression model for speed y_{ij}, can be expressed as

Level-1

$$y_{ij} = \beta_{0i} + \beta_{1i}x_j + \beta_{2i}x_j^2 + \beta_{3i}x_j^3 + \beta_{4i}x_j^4\, e_{ij} = \mu_{ij} + e_{ij}$$

$$\text{with, } \mathrm{E}(y_{ij}) = \mu_{ij}, \text{ and with } e_{ij} \sim N(0, \sigma^2) \qquad \textit{equation}(1)$$

The likelihood function is given by

$$f(y_{ij}) \propto \underset{i}{\pi}\, \underset{j}{\pi} (\sigma_e^2)^{-\frac{1}{2}} \exp\left\{ -\frac{1}{2\sigma_e^2}(y_{ij} - \mu_{ij})^2 \right\} \qquad \textit{equation}(2)$$

The joint posterior distribution (Equation. 7) for all model parameters was obtained by multiplying the likelihood function (Equation. 2) with the priors (Equation.3) and the hyper-priors (Equation. 4 to 6).

Level-2

$$\beta_{0i} \sim N(\mu_0, \sigma_0^2)$$

$$p(\beta_{0i}) \propto (\sigma_0^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2\sigma_0^2}(\beta_{0i} - \mu_0)^2 \right)$$

$$p(\beta_{1i}) \propto (\sigma_1^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2\sigma_1^2}(\beta_{1i} - \mu_1)^2 \right)$$

$$p(\beta_{2i}) \propto (\sigma_2^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2\sigma_2^2}(\beta_{2i} - \mu_2)^2 \right)$$

$$p(\beta_{3i}) \propto (\sigma_3^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2\sigma_3^2}(\beta_{3i} - \mu_3)^2 \right)$$

$$p(\beta_{4i}) \propto (\sigma_4^2)^{-\frac{1}{2}} \exp\left(-\frac{1}{2\sigma_4^2}(\beta_{4i} - \mu_4)^2 \right) \qquad \textit{equation}(3)$$

$$\sigma_e^2 \sim inversegamma\,(a,b)\, or\; IG(a,b) \qquad equation(4)$$

$$Var\left(\sigma_e^2\right)=\frac{b^2}{(a-1)^2(a-2)}, \quad a>2$$

For large $Var(\sigma_e^2) and\ \mathrm{E}(\sigma_e^2) \approx \mathrm{MSE}_{classical\, regression}$,

$a=$ 2.001 and $b=(a+1) * \mathrm{MSE}_{classical\, regression}$

Level-3

$$\mu_0 \sim N(m1, S_1^2)$$

$$\mu_1 \sim N(m2, S_2^2)$$

$$\mu_2 \sim N(m3, S_3^2)$$

$$\mu_2 \sim N(m3, S_3^2)$$

$$\mu_2 \sim N(m3, S_4^2) \qquad equation(5)$$

$$\sigma_r^2 \sim IG(p_i, r_i) \text{ , where } r=0 \text{ to } 5 \qquad equation(6)$$

Joint posterior distribution

$$\begin{aligned} & p(\beta_{01},\beta_{02},\beta_{03},\beta_{11},\beta_{12},\beta_{13},\beta_{21},\beta_{22},\beta_{23},\sigma_e^2,\mu_0,\mu_1,\mu_2,\sigma_0^2,\sigma_1^2,\sigma_2^2 \mid y) \\ & = N(y \left| \beta_{0i},\beta_{1i},\beta_{2i},\sigma_e^2)*N(\beta_{0i}\right|\mu_0,\sigma_0^2) * N(\beta_{1i}\left|\mu_1,\sigma_1^2)*N(\beta_{2i}\right|\mu_2,\sigma_2^2)* \\ & IG(\sigma_e^2 \left| a,b) * N(\mu_0 \right| \overline{y}) * N(\mu_1) * N(\mu_2) * IG(\sigma_0^2) * IG(\sigma_1^2) * IG(\sigma_2^2) \qquad equation(7) \end{aligned}$$

The following conditional distributions (Equation. 8 to 14) were derived from Equation. 7 for the model parameters.

Conditionals for β_{ki} $(k=0\, to\, 4)$

$$A_{oi}=\frac{\sigma_0^2 J\overline{y}_i-\beta_{1i}\sigma_0^2 J\overline{x}-\beta_{2i}\sigma_0^2\sum_j x_j^2-\beta_{3i}\sigma_0^2\sum_j x_j^2-\beta_{4i}\sigma_0^2\sum_j x_j^4+\mu_0\sigma_e^2}{(J\sigma_0^2+\sigma_e^2)}$$

$$B_{0i}^2=\frac{\sigma_e^2\sigma_0^2}{(J\sigma_0^2+\sigma_e^2)}$$

$$p(\beta_{0i}\left|all\right.)=N(A_{0i},B_{0i}) \qquad equation(8)$$

$i=1$ *to* 4 (total number of drivers)

$$A_{1i} = \frac{\sigma_1^2 \sum_j y_{ij} x_j - \beta_{0i}\sigma_1^2 J\overline{x} - \beta_{2i}\sigma_1^2 \sum_j x_j^3 - \beta_{3i}\sigma_1^2 \sum_j x_j^4 - \beta_{4i}\sigma_0^2 \sum_j x_j^5 + \mu_1\sigma_e^2}{(J\sigma_1^2 + \sigma_e^2)}$$

$$B_{1i}^2 = \frac{\sigma_1^2\sigma_e^2}{(\sum_j x_j^2)\sigma_1^2 + \sigma_e^2}$$

$$p(\beta_{ij} \,|all) = N(A_{1i,} B_{1i}) \qquad equation(9)$$

$$i = 1 \; to \; 4$$

$$A_{2i} = \frac{\sigma_2^2 \sum_j y_{ij} x_j^2 - \beta_{0i}\sigma_2^2 \sum_j x_j^2 - \beta_{1i}\sigma_2^2 \sum_j x_j^3 - \beta_{3i}\sigma_2^2 \sum_j x_j^5 - \beta_{4i}\sigma_0^2 \sum_j x_j^6 + \mu_2\sigma_e^2}{(J\sigma_0^2 + \sigma_e^2)}$$

$$B_{2i}^2 = \frac{\sigma_2^2\sigma_e^2}{(\sum_j x_j^2)\sigma_2^2 + \sigma_e^2}$$

$$p(\beta_{ij} \,|all) = N(A_{2i,} B_{2i}) \qquad equation(10)$$

$$i = 1 \; to \; 4$$

$$A_{3i} = \frac{\sigma_3^2 \sum_j y_{ij} x_j^3 - \beta_{0i}\sigma_3^2 \sum_j x_j^3 - \beta_{1i}\sigma_3^2 \sum_j x_j^4 - \beta_{2i}\sigma_3^2 \sum_j x_j^5 - \beta_{4i}\sigma_3^2 \sum_j x_j^7 + \mu_3\sigma_e^2}{(J\sigma_3^2 + \sigma_e^2)}$$

$$B_{3i}^2 = \frac{\sigma_3^2\sigma_e^2}{(\sum_j x_j^2)\sigma_3^2 + \sigma_e^2}$$

$$p(\beta_{ij} \,|all) = N(A_{3i,} B_{3i}) \qquad equation(11)$$

$$i = 1 \; to \; 4$$

$$A_{4i} = \frac{\sigma_4^2 \sum_j y_{ij} x_j^4 - \beta_{0i}\sigma_4^2 \sum_j x_j^4 - \beta_{1i}\sigma_4^2 \sum_j x_j^5 - \beta_{2i}\sigma_4^2 \sum_j x_j^6 - \beta_{3i}\sigma_4^2 \sum_j x_j^7 + \mu_4\sigma_e^2}{(J\sigma_4^2 + \sigma_e^2)}$$

$$B_{4i}^2 = \frac{\sigma_4^2\sigma_e^2}{(\sum_j x_j^2)\sigma_4^2 + \sigma_e^2}$$

$$p(\beta_{ij} \,|all) = N(A_{4i,} B_{4i}) \qquad equation(12)$$

$$i = 1 \; to \; 4$$

$$p(\sigma_e^2 \,|all) = IG\left[\frac{J\,\mathrm{N}}{2} + a, \frac{1}{2}\left[\Sigma\Sigma(y_{ij} - \mu_{ij})^2 \right]^2 + b \right]$$

$$A_{\mu k} = \frac{\sigma^2 \sum \beta_{ki} + \sigma_k^2 m}{\mathrm{N}\sigma^2 + \sigma_k^2}$$

$$B_{\mu k}^2 = \frac{\sigma_k^2 \sigma^2}{(\mathrm{N}\sigma^2 + \sigma_k^2)}$$

$$p(\mu_k \,|all) = N(A_{\mu k}, B_{\mu k}) \qquad equation(13)$$

$$k = 0 \ to \ 4 \ for \ 5 \ betas$$

$$P_k = 2 + p$$

$$Q_k^2 = r + \frac{1}{2}\sum_i (\beta_{ki} - \mu_k)^2$$

$$p(\sigma_k \,|all) = IG(P_k, Q_k^2) \qquad equation(14)$$

$$p = 0.01, \ r = 0.01$$

$$k = 0 \ to \ 4 \ for \ 5 \ betas$$

Since the conditional distributions were not implicit functions, simulation was necessary to draw the parameters from the conditionals. For this, we chose to perform Gibbs sampling over 10000 iterations. The initial values of all parameters were taken to be the estimates from classical regression. The first 1000 simulated values were discarded as burn-in to get stabilized draws. A burn-in period is that beyond which values of subsequent draws/updates become steady and hetero-scedasticity vanishes. Subsequent draws from the stabilized period were found to be auto-correlated with a lag of 11. Therefore, every fifteen draws were retained while discarding the rest to obtain a distribution with no autocorrelation (Figure 6.5) This strategy of reducing autocorrelation by retaining every 15th point after the burn-in period is called thinning the output. Figure 6.6 shows trace plot of β_0 for all drivers showing the convergence. The green, red, pink and blue colors correspond to Driver 1 through 4.

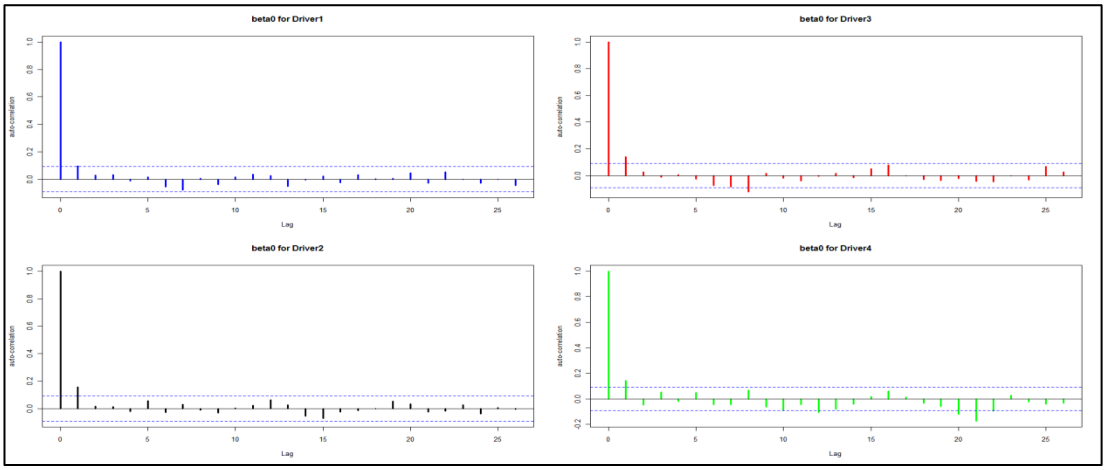

Figure 6.5: Auto-correaltion plot of steady state β_0 after thinning

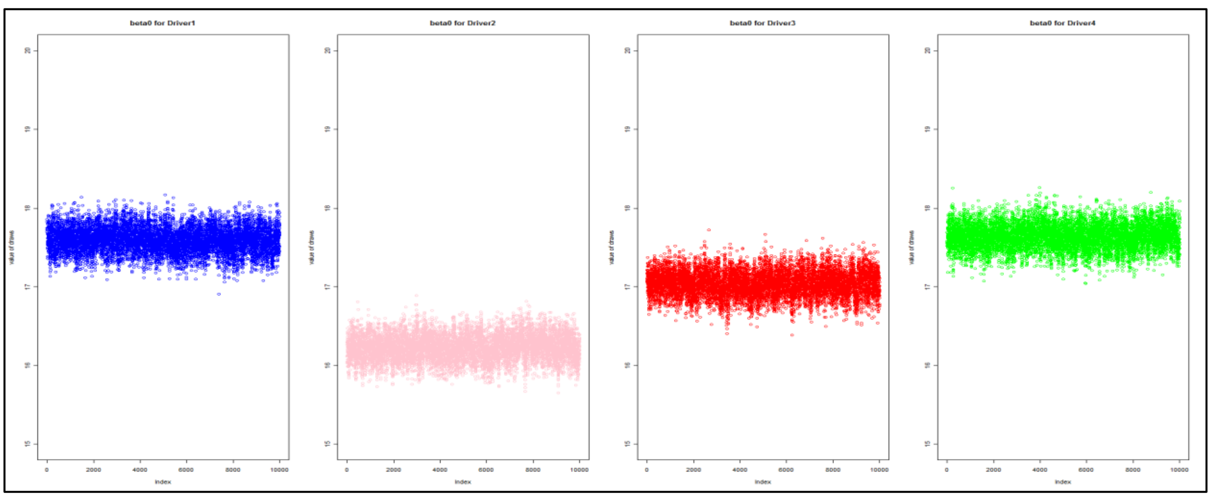

Figure 6.6: Plot of every 15 draws of steady state β_0 for all drivers.

6.3.2 Results and discussion

Figure 6.9 shows the model speed profiles for the four drivers. On an average, driver-1 drove faster than Driver-2. Initial speed of Driver-4 was about the lowest one; however, he/she attained the highest speed at upstream. This indicated Driver-4 had harder/aggressive acceleration behavior that is likely to produce higher emissions. Also, the individual speed models (Figure 6.9) indicate that all drivers drove at speed higher than 15 mph, the circulating speed limit of the roundabout.

The individual betas (Figure 6.8 - 6.9) that form the regression equation have significantly different distributions. This indicates that each driver had a unique speed profile which cannot be represented by a single (fourth degree polynomial) regression model. In order to perform a predictive check, certain quantities of interest called discrepancy statistics are defined based on the research objective. Posterior predictive distribution is obtained from the following equations.

Replication-1

$p(y^{rep}|y) = \int p(y^{rep}|\theta)\ \ p(\theta|y)d\theta$……………………….equation (13)

or, $p(y^{rep}|y) = \int \text{sampling distribution } \mathbf{x} \text{ Posterior distribution } d\theta$

Replication- n

$p\left(y_n^{rep}\middle|y_{n-1}^{rep}\right) = \int p\left(y_n^{rep}\middle|\theta\right)\ \ p(\theta|y_{n-1}^{rep})d\theta$……………………….equation (14)

Here, yrep represents replicated values of y. Subsequent replications of y are obtained from existing posterior predictive distribution as shown in equation 14. Each step requires performing Gibbs sampling to obtain steady, serially uncorrelated (no auto-correlation) replications. Discrepancy statistics, as defined above, are computed from posterior predictive distribution at each step of replication. The size of this distribution is equal to the number of replications. In a posterior predictive check, the hypothesis being tested is if the chosen discrepancy statistic came from the replicated data.

In order to test for model fit and reliability, two discrepancy statistics were defined.

The maximum difference in median of β0 among driver. (β0 is the mean speed for a given trip-part)

The maximum acceleration of Driver-1. Acceleration is derived by taking the first difference of model speedmodel (acceleration = speed[t] model –speed[t-1] model).

Figure 6.10 shows the posterior predictive check for maximum difference in median of β0 among drivers. The observed value was 1.45 which does not seem to have come from the distribution generated from replicated data. Figure 6.11 depicts the posterior predictive check for maximum acceleration corresponding to Driver-1. The observed value of 1.29 was likely to come from the distribution generated from replicated data. These results imply a reasonably well model.

Table 6.2 gives the quartiles for betas corresponding to each driver.

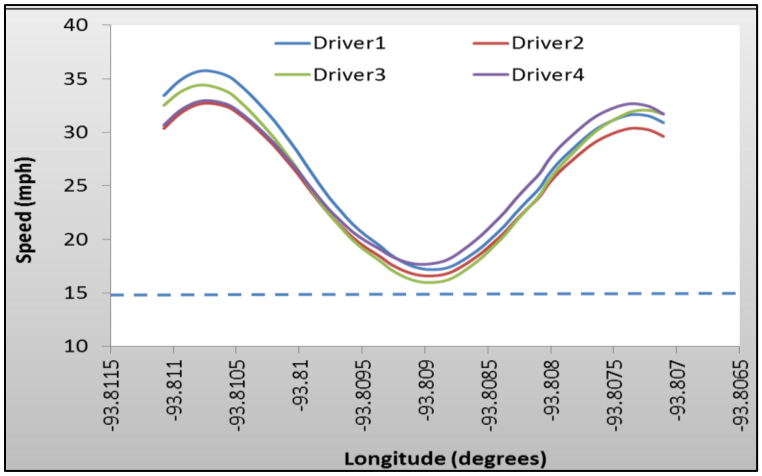

Figure 6.7: Regression model for speed profile of each driver

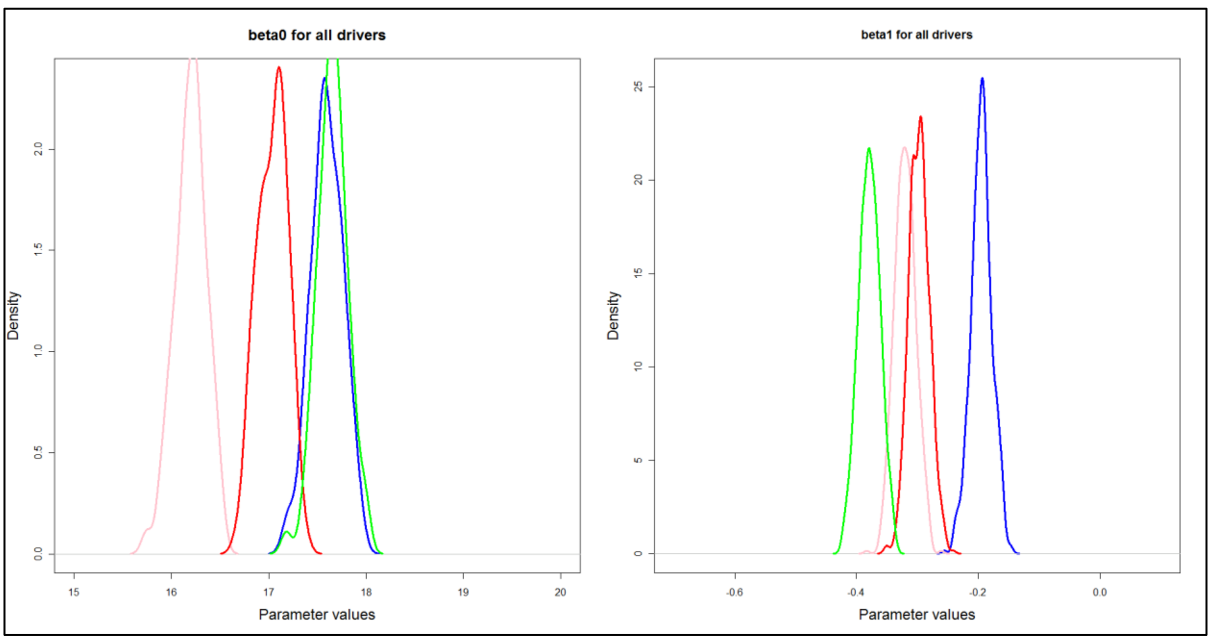

Figure 6.8: β_0 and $\beta_1$for all drivers

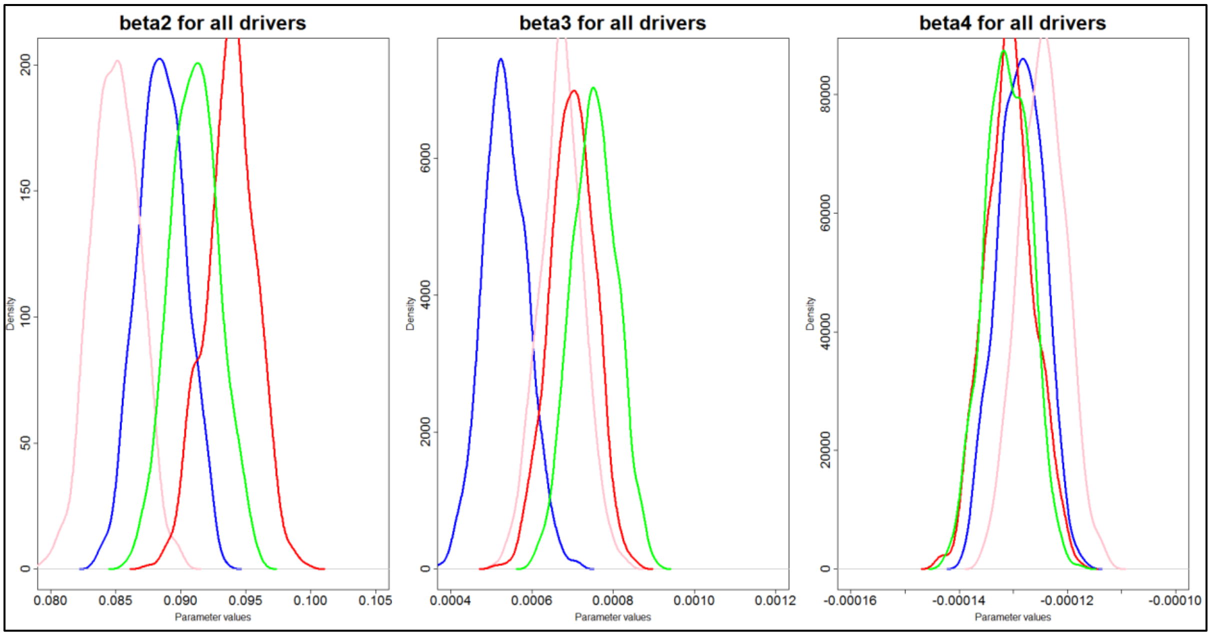

Figure 6.9: β2,β3, and β4 for all drivers

6.3.3 Posterior predictive check

In a Bayesian context, "posterior predictive" check implies comparing predictive distribution to the observed data (Gelman et al. 1995). It is used to produce inference about key quantities of interest or to test model fit (Lynch and Western, 2004).

In order to perform a predictive check, certain quantities of interest called discrepancy statistics are defined based on the research objective. Posterior predictive distribution is obtained from the following equations.

Replication-1

$$p(y^{rep}|y) = \int p(y^{rep}|\theta)\ \ p(\theta|y)d\theta \text{.............................equation (13)}$$

$$or, \qquad p(y^{rep}|y) = \int \text{sampling distribution } \mathbf{x} \text{ Posterior distribution } d\theta$$

Replication- n

$$p(y_n^{rep}|y_{n-1}^{rep}) = \int p(y_n^{rep}|\theta)\ \ p(\theta|y_{n-1}^{rep})d\theta \text{............................equation (14)}$$

Here, y^{rep} represents replicated values of y. Subsequent replications of y are obtained from existing posterior predictive distribution as shown in equation 14. Each step requires performing Gibbs sampling to obtain steady, serially uncorrelated (no auto-correlation) replications. Discrepancy statistics, as defined above, are computed from posterior predictive distribution at each step of replication. The size of this distribution is equal to the number of replications. In a posterior predictive check, the hypothesis being tested is if the chosen discrepancy statistic came from the replicated data.

In order to test for model fit and reliability, two discrepancy statistics were defined.

1) The maximum difference in median of β_0 among driver. (β_0 is the mean speed for a given trip-part)

2) The maximum acceleration of Driver-1. Acceleration is derived by taking the first difference of model $speed_{model}$ (acceleration = $speed[t]_{model} - speed[t-1]_{model}$).

Figure 6.10 shows the posterior predictive check for maximum difference in median of β0 among drivers. The observed value was 1.45 which does not seem to have come from the distribution generated from replicated data. Figure 6.11 depicts the posterior predictive check for maximum acceleration corresponding to Driver-1. The observed value of 1.29 was likely to come from the distribution generated from replicated data. These results imply a reasonably well model.

Table 6.2: Quartiles of various betas for all drivers

Quartiles	5%	25%	50%	75%	95%
Beta0					
Driver-1	17.37	17.53	17.64	17.76	17.92
Driver-2	16.79	16.95	17.05	17.15	17.31
Driver-3	15.97	16.12	16.23	16.34	16.49
Driver-4	17.33	17.49	17.6	17.71	17.86
Beta1					
Driver-1	-0.41	-0.39	-0.38	-0.37	-0.35
Driver-2	-0.32	-0.31	-0.3	-0.28	-0.27
Driver-3	-0.35	-0.33	-0.32	-0.31	-0.29
Driver-4	-0.23	-0.21	-0.2	-0.18	-0.17
Beta2					
Driver-1	0.087922	0.089794	0.091054	0.092303	0.094194
Driver-2	0.081826	0.083556	0.084738	0.085936	0.087652
Driver-3	0.090795	0.092553	0.093768	0.094995	0.096637
Driver-4	0.085377	0.087223	0.088531	0.089803	0.091553
Beta3					
Driver-1	0.000667	0.000719	0.000756	0.000793	0.000847
Driver-2	0.000580	0.000631	0.000669	0.000704	0.000757
Driver-3	0.000608	0.000661	0.000699	0.000734	0.000785
Driver-4	0.000445	0.000500	0.000537	0.000573	0.000627
Beta4					
Driver-1	-0.00014	-0.00013	-0.00013	-0.00013	-0.00012
Driver-2	-0.00013	-0.00013	-0.00012	-0.00012	-0.00012
Driver-3	-0.00014	-0.00013	-0.00013	-0.00013	-0.00012
Driver-4	-0.00014	-0.00013	-0.00013	-0.00013	-0.00012

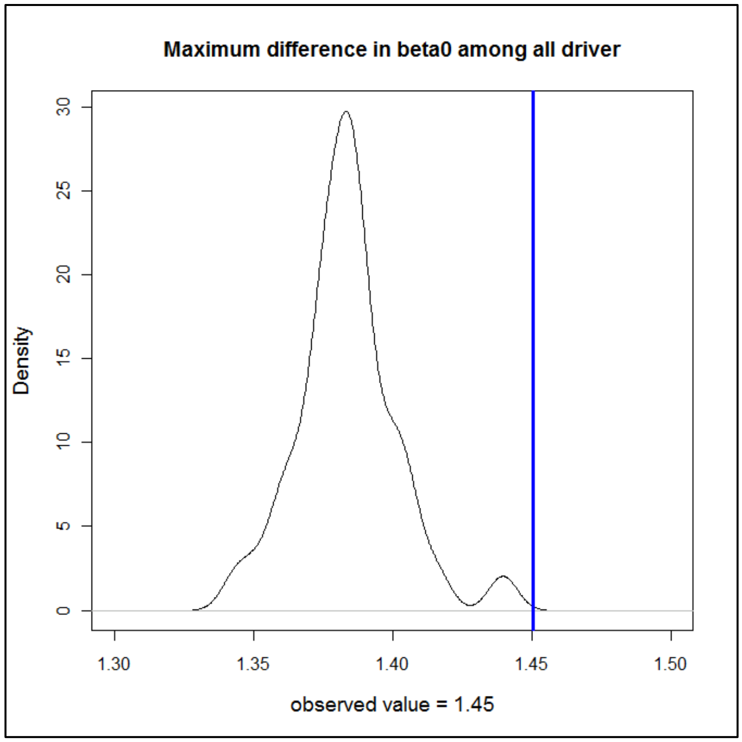

Figure 6.10: Posterior predictive check: maximum β0 among drivers

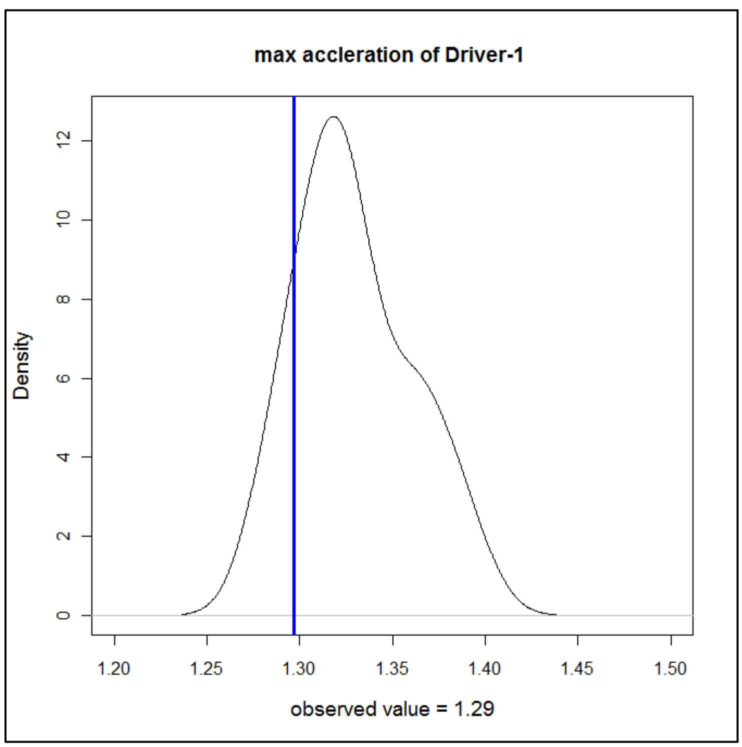

Figure 6.11: Posterior predictive check: Maximum acceleration of Driver-1

6.3.4 Posterior prediction of mean speed at yield point of roundabout

For each driver, mean speed at the yield point of the roundabout was estimated from posterior predictive distribution. Results show that the speed at the yield point was significantly different among drivers (Figure 6.12). They are expected to accelerate differently to attain the free flow (cruise) speed beyond the region of influence of the roundabout.

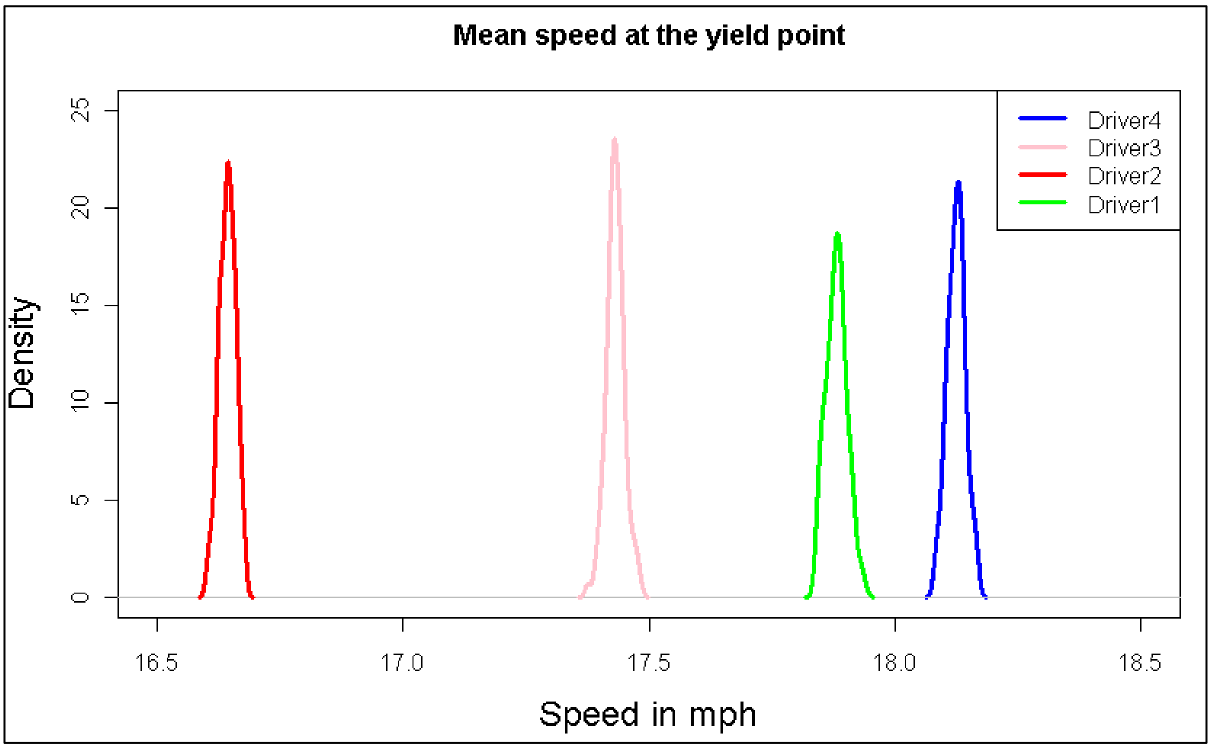

Figure 6.12: Posterior prediction of mean speed at the yield point of roundabout for all drivers

6.4 Summary

The primary objective of this dissertation was to investigate the impact of driving behavior on emissions. In this chapter, speed profiles at a roundabout were modeled. An attempt was made to fit a fourth degree regression curve to model the speed profiles. The model fitted the observations with reasonable accuracy.

Results show that the speed profiles at the roundabout were not similar among drivers. This implied that driver must be taken as a random variable while modeling vehicle activity and emissions. This supports the assumptions made in a previous study (Ericsson, 2000).

Also, mean speeds at the yield point of the roundabout were also different. If a larger number of drivers were used in the study, the difference is likely to be greater (for example 2-5 mph). This may result in significantly higher emissions for some drivers. Higher speed may also have safety implications.

Modeling speed is an important aspect of characterizing driving behavior (TRB-C151, 2011). The methodology/model used in this chapter can be extended to modeling operating speed at other intersections types. Also, based on the models generated, classification of driving behavior and corresponding emissions can be performed.

CHAPTER 7. Conclusions and Recommendations

This chapter summarizes the findings and contributions of this study comprising driving behavior at traffic control devices. The assumptions adopted as well as limitations of the study are discussed. Recommendations for future work are also offered.

7.1 Findings

In this dissertation, driving behavior was studied at three levels. First, parameters were explored to explain driving behavior among individual drivers and traffic control devices. Second, driving behavior was compared between pairs of traffic control devices using MANOVA. Lastly, second-by-second driving behavior of individual drivers was modeled and analyzed. The following were the key findings from the study:

1.) Two groups of drivers were identified among the four drivers based on the driving behavior parameters.

2.) Driving behavior at roundabout and all-way-stop were similar as seen from the distributions of driving behavior parameters. However, statistical tests (MANOVA) done using driving behavior parameters summarized over individual traffic control devices revealed that there is a difference. The implication is that rather than averaging the emission factor over the routes, separate emission factors must be developed for each traffic control device for better accuracy of emissions estimates.

3.) In this study, speed profiles of different drivers were modeled using Bayesian hierarchical regression. It was found that each driver had a unique speed profile.

4.) Speed at the yield point of roundabout was significantly different across drivers. The maximum difference was estimated as 1.5 mph. With more number of drivers, this difference is likely to increase resulting in difference in emissions from driver to driver.

7.2 Key contributions

1.) This study was the only one of this type where second-by-second driving behavior was modeled. Models that provides second-by-second driving behavior can be useful for identifying driving behavior at higher resolution of space. This may help identify hot spots or aggressive driving on the road.

2.) Speed profile of individual drivers was modeled using Bayesian method is capable of providing non-linear parameters with confidence interval. Classical methods fail to provide confidence interval for non-linear parameter. In this study, there was variability in speed from trip to trip. Also, since there was variability in speed within driver and between drivers, a multilevel model was chosen. The research highlights the use of Bayesian Hierarchical (Multi-level model) framework for modeling instantaneous speed. Although, findings are limited to the given driver-vehicle combinations, the methodologies used in this research would be useful in similar situations and beyond.

3.) This work identifies the utility of gas pedal and brake pedal parameters to characterize driving behavior. These parameters corroborated other common driving behavior parameters (speed, acceleration and VSP).

4.) The research identifies that driving behaviors at various traffic control devices are significantly different. Trip-part, the portion of driving in the region of influence of traffic control devices, can be used for developing driving cycles. Selecting trip-parts randomly and appending them one after another based on some conditions (e.g. maximum acceleration) can be useful in developing driving cycles.

5.) The study gives more insight into driving behavior which is highly correlated with vehicular emissions.

In this study, numerous assumptions were made to compensate for the non-ideal situation. The following section presents assumptions that formed a basis of analysis in this study.

7.3 Assumptions

As in all studies, some assumptions had to be made in order to control the parameters of the study. The following assumptions were made in order in this research. These assumptions were not tested and if conditions actually differed from these assumptions, it may have affected the analysis results.

1.) It was assumed that the drivers were driving in a normal state of mind devoid of boredom or fatigue.

2.) Drivers were not affected by the time of the day or day of the week.

3.) The vehicle was assumed to be functioning properly all the time.

4.) On one of the data collection day, the pavement was covered with a layer of water due to rain. The amount of rain was judged to be minor and it was assumed that there was no significant change in road friction due to wet pavement and that there were no changes in driver behavior.

7.4 Limitations and challenges faced

1.) High variability associated with on-road emissions (Frey et al., 1997; Bammi, 2001) only allows relative measures of emissions instead of absolute values.

2.) Only four drivers were considered which reduces the scope of extending the results to the overall population.

3.) Data collection was done on single roundabout, all-way-stop and traffic signal. In order to validate the findings, a higher number of traffic control devices should be tested.

4.) The analysis is limited to driving behavior on a single mid-size passenger car. The research conclusions may not be applicable to driving behavior associated with other common vehicles.

5.) There are measurement limitations associated with the GPS used in the study.

6.) GPS do not provide reliable data on altitude and it was not possible to conduct a survey of road grade along the route. There were no adverse changes in elevation but acceleration and deceleration can be affected by road grade. This limits the method of deriving gaspad and brakepad using acceleration. Some recommendation for overcoming this limitation is provided in the next section.

The study presented new findings while corroborating existing findings. It opened up new research directions. In the next section, recommendation for advancing the research is presented.

7.5 Recommendations for future research

This study offers the following recommendations for furthering the research:

1.) Driving behavior associated with different vehicles is likely to be different. For example, a typical driver would drive a hybrid car differently in urban roads by making use of the regenerative braking system. Further, driving behavior for heavy duty vehicle can be studied in order to understand how heavy vehicle drivers maneuver curves.

2.) Pressure sensor can be installed on the pedals for precise estimations of gas pedal pressure and brake pedal pressure.

3.) Emission factors specific to a traffic control device can be developed.

4.) The method used in the study for modeling individual driver speed can be extended to modeling speed at curves for evaluating safety and operation at curves.

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