A UTILITY-BASED AGENT FOR VEHICLE DRIVER BEHAVIOUR MODELLING

BY

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DECLARATION

Student's Declaration:

This thesis entitled "A Utility-Based Agent for Vehicle Driver Behaviour Modelling" is my original work and has not been presented in any other University or Institution for consideration of any certification.

James Obuhuma Imende PHD/CI/00054/2014	____________________ Signature	____________________ Date

Supervisors' Declaration:

We confirm and certify that the work reported in this thesis was carried out by the candidate under our supervision as University supervisors.

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DEDICATION

I dedicate this work to the Almighty God and to my lovely daughter Mildred, my dad and to my late mum.

ABSTRACT

Knowledge on driver behaviour is a major factor that can possibly aid in future strategies for minimising if not fully controlling road fatalities. The behaviour of human vehicle drivers is the main cause of road accidents and is also the factor which has so far proved to be the most difficult to establish and model. Studies conducted on driver behaviour modelling have been limited by five factors: study methodology; vehicle model compatibility; cost; overestimation of critical driving events; and scope for driver behaviour monitoring. Probabilistic reasoning and intelligence, which are critical in modelling under stochastic environments are lacking in the applied methodologies. Fortunately, a combination of computing and communication technologies now makes it possible to model the behaviour of drivers operating in complex environments. The main objective of the research was to model human vehicle driver behaviour using a utility-based agent. To realise this objective, the research identified parameters that describe the behaviour of a human vehicle driver operating under diverse environments, formulated a vehicle driver behaviour dataset and developed and evaluated a vehicle driver agent that can operate in a complex environment. A sample of 30 drivers was used, with tonnes of data collected and analysed. Vehicle position coordinates, speed, direction, altitude, time and a reflected signal signifying the presence of an obstacle were collected using the Global Positioning System (GPS) comprising of satellites, GPS receivers and a server. Data analysis generated a driver behaviour dataset that was used in the preparation of the driver agent through three main phases: training, validation and testing. The driver agent was founded on Mixture Models with Bayesian inferencing techniques that performed driver behavioural pattern recognition and predictive analyses. The agent’s actions under dynamic conditions were evaluated against sets of performance standards, yielding mean success rates of over 68% accuracies and over 70% F-scores, +/- 5. This was an indicator of the appropriateness of the data collection tools and techniques, data analysis algorithms and the driver behaviour dataset. The significance of the study is three-fold. First, the function of the system could be extended to providing advisory services to drivers in real-time. Second, data gathered from the system could be used by road safety stakeholders to vet drivers and to diagnose causes of road accidents. Finally, the resulting knowledge-base could establish standards of rationality in driving and/or formulate rules for use in driverless vehicle control systems.

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LIST OF ABBREVIATIONS

2TBN	Two-Timeslice Bayesian Network
AC	Alternating Current
ANOVA	Analysis of Variance
ARM	Advanced RISC Machines
ASR	Automatic Speech Recognition
AVL	Automatic Vehicle Location
AVR	Alf and Vegard's RISC
BDD	Berkeley DeepDrive
BN	Bayesian Network
CAN-Bus	Controller Area Network - Bus
COM	Communication
CRSS	Centre for Robust Speech System
DBN	Dynamic Bayesian Network
DC	Direct Current
DCU	Data Collection Unit
DOF	Degree of Freedom
DOP	Dilution of Precision
DSL	Dynamic Speed Limit
DSRC	Dedicated Short Range Communication
DTW	Dynamic Time Warping
EM	Expectation Maximisation
FFT	First Fourier Transforms
FMCW	Frequency-Modulated Continuous-Wave
Fn	False Negative
Fp	False Positive
GMM	Gaussian Mixture Model
GPRMC	Recommended Minimum Specific GPS/Transmit Data
GPRS	General Packet Radio Service
GPS	Global Positioning System

GSM	Global System for Mobile
HCA	Hierarchical Cluster Analysis
HDOP	Horizontal Dilution of Precision
HMM	Hidden Markov Model
ICSP	In-Circuit Serial Programming
IDE	Integrated Development Environment
IP	Internet Protocol
IRTAD	International Traffic Safety Data and Analysis Group
ITS	Intelligent Transportation Systems
KNN	K-Nearest Neighbour
LIDAR	Light Imaging Detection and Ranging
MANET	Mobile Ad-hoc Network
MANOVA	Multiple Analysis of Variance
MSP	Mixed Signal Processor
MT	Maneuver Time
MVDR	Minimal Variance Distortionless Response
NC	Normally Connected
NGSIM	Next Generation Simulation
NMEA	National Marine Electronics Association
NO	Normally Open
OBD	On-Board Diagnostics
PCA	Principal Component Analysis
PCB	Printed Circuit Board
PIC	Peripheral Interface Controller
PRT	Perception Reaction Time
PSV	Public Service Vehicle
PWM	Pulse Width Modulation
RADAR	Radio Detection and Ranging
RISC	Reduced Instruction Set Computer
RPM	Revolutions per minute
RSA	Road Safety Authority

RSU	Roadside Unit
SFFS	Sequential Floating Forward Selection
SIM	Subscriber Identity Module
SMS	Short Message Services
SPDT	Single Pole Double Throw
SQL	Structure Query Language
SSD	Stopping Sight Distance
TCP	Transmission Control Protocol
THW	Time Headway
Tn	True Negative
Tp	True Positive
TTC	Time-to-Collision
TTL	Time to Live
UDP	User Datagram Protocol
USA	United States of America
USB	Universal Serial Bus
USL	Uniform Speed Limit
UTC	Coordinated Universal Time
UTDrive	The Smart Vehicle Project, University of Texas at Dallas
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VANET	Vehicular Ad-hoc Network
VMS	Variable Message Sign
VRC	Vehicle-to-Roadside Communication
VSL	Variable Speed Limit
WHO	World Health Organisation

DEFINITION OF TERMS

Agent: An entity that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors.

Driver Behaviour Model: A representation of a human vehicle driver.

Machine Learning: An application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.

Model: A model is an abstraction of reality or a representation of a real object or situation. In other words, a model presents a simplified version of something.

Modelling: The act of coming up with a model of something. In the context of this study, the main objective was to come up with a model of a human vehicle driver.

Public Service Vehicles: A category of vehicles that serves the public, mostly at a fee i.e. some ferry passengers at a fee.

Private Service Vehicles: A category of vehicles that are mostly individually owned and that are dedicated for personal or private kind of usage.

Software Agent: A computer based implementation of an agent.

Utility-Based Agent: A type of agent that uses a model of the world, along with a utility function that measures its preferences among states of the world by choosing actions that leads to the best-expected utility, where expected utility is computed as an average of all possible outcome states, weighted by the probability of the outcome.

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CHAPTER 1
INTRODUCTION

This chapter lays a foundation to the study by outlining the background of the study, problem statement and its justification, the study hypothesis, objectives and research questions. The chapter further describes assumptions and limitations leading to the scope of the study. The significance of the study is also outlined.

1.1 BACKGROUND OF THE STUDY

Road traffic injuries are estimated to be the eighth leading cause of death globally [1], [2]. According to the World Health Organisation's global status reports on road safety for the years 2013, 2015 and 2018, the total number of road traffic deaths remains unacceptably high at over a million people annually [1]–[3]. Majority of the victims are vulnerable road users, including: pedestrians, motorcyclists and cyclists. In addition, nearly one-third of deaths are passengers, many of whom are killed in unsafe forms of public transportation. Worryingly, the World Health Organisation predicts that road traffic injuries will become the fifth leading cause of death by the year 2030 unless urgent action is taken [4].

Studies have established that road traffic accidents may be attributed to a combination of four main factors, namely: structures of roads; states of roads; states of vehicles; and behaviours of human vehicle drivers [5], [6]. The structure and state of the road includes terrain, type and condition of the road, incline of the road, intersections among other factors. On the other hand, the state of the vehicle relates to the maintenance level of the vehicle. Each of these factors has some impact on road safety. According to the Road Safety Authority [5], the contributory factors listed by An Garda Siochana on collision report between 2007 and 2011 showed that: driver error accounted for 84.8% of all contributory factors identified in fatal collisions; pedestrian error accounted for 7.8%; road factors accounted for 4.6%; environmental factors accounted for 2.5% while vehicle mechanical factors accounted for 0.3%. A different study carried out in the year 2010 showed that human factors accounted for 74% of road crashes in Tanzania, vehicle mechanical factors accounted for 12% while road conditions accounted for 14% [6]. Considering the aforementioned facts, the behaviour of human vehicle drivers stands out as a leading factor to road crashes. It is worth noting that potentially aggressive driving behaviour has been established to be currently a leading cause of traffic fatalities in the United States of America with drivers being unaware that they commit the actions daily [7]. Over 60% of fatalities on highways, urban and rural roads could be avoided if there were measures for alerting vehicle drivers or road users of looming danger before it occurs [8]. It is vital to build up mobility models and algorithms for safe and efficient environment.

Mechanisms to notify and alert drivers in realtime on the status of roads ahead of them are hence paramount. Luckily, technological advances make innovations easier with feasible solutions to complex problems. For instance, Intelligent Transportation Systems (ITS) are a set of technological solutions used to improve performance and road safety [9]. Such systems could be applied in predicting and alerting drivers on undesirable situations in their operational environment [9]. One such great application, is the use of vehicular network systems in ITS where future vehicles would be embedded with an On-Board Unit (OBU), Wireless Sensors, GPS, and GPS receivers and supplemented with road side units (RSUs) to provide intelligence among vehicles [10].

The exchange of safety messages among moving vehicles within a specific timeframe and distance ranges using Vehicular Ad-hoc Networks (VANETs) is attracting lots of attention in various sectors, including, automobile industries, governmental organisations, telecommunication sectors and academia [10]. Thus, contemporary research in the transport and road safety industry is experiencing a paradigm shift towards intelligent vehicles as a way to transform the transportation industry. This is resulting in the evolution of self-driving and highly automated vehicles that are required to navigate smoothly while avoiding obstacles and understanding high levels of scene semantics [11].

Despite all these advances in car technology leading to self-driving cars, human vehicle drivers still remain to be critical agents on world roads. Their behaviour in terms of driving styles impacts heavily on the behaviour of other road users. Furthermore, the behaviour also has a direct correlation to road safety. Ohn-Bar and Trivedi [11] explored a human element in three domains, namely, human in the cabin, human around the vehicle and human in surrounding vehicles. Each of the three perspectives have an influence on a vehicle driver on the wheel. It is hence vital for any intelligent solution for vehicle driver modelling to put this into consideration. Ohn-Bar and M. M. Trivedi's [11] study was just a review of other studies with a discussion of techniques that could be applied per domain.

To model the behaviour of a human vehicle driver requires clear mechanisms to monitor and collect behavioural parameters in realtime, mechanisms to analyse the data and finally mechanisms to utilise the outcome in the development of the model. It is worth noting that vehicle drivers operate under diverse and dynamic environments full of other agents. A vivid picture of a vehicle driver behaviour can only be established if such behaviour is monitored in realtime and over varied operational environments. Hence, studies on vehicle driver behaviour merit attention. It is worth noting that vehicle drivers operate under dynamic, nondeterministic, strategic and stochastic environments. Such environments are difficult to monitor, analyse and model. Fortunately, the rapid technological changes are creating avenues for automation of complex processes.

Notable attempts have been made in the recent past towards modelling vehicle driver behaviour. These studies include: a simulator model by Wakitani et al. [12], a neural car-following model by Morton, Wheeler and Kochenderfer [13], a steering model for predicting driver behaviour by Schnelle, Wang, Su and Jagacinski [14], a highly automated driver agent by Noh et al. [15] among other studies. Whereas most of the recent studies are simulator-based, some of them have considered using vehicles equipped with multiple sensors as others focus on the use of preexisting datasets. Extensive scientific investigations, for instance, have seen deployments of instrumented vehicles with improved safety capabilities in Asia, America and Europe [16]. The UTDrive project is such an example whose principal objectives were to collect and research rich multi-modal data recorded in actual car environments for analysing and modelling driver behaviour [17], [18]. The platform has been applied in several studies on driver behaviour. For example studies by Li, Jain and Busso [19], Sathyanarayana, Boyraz and Hansen [20], Sathyanarayana et al. [21]. In spite of these, a major issue worth addressing is the integration of major data streams associated with driving styles in advanced data analytics techniques geared towards modelling driver behaviour.

1.2 PROBLEM STATEMENT

A number of notable factors impact on road safety. A significant number of studies have identified driver behaviour as the major cause of traffic injuries worldwide. Unfortunately, the behaviour of vehicle drivers has so far proved to be the most difficult factor to monitor, analyse and model. The complexity in modelling human vehicle driver behaviour stems from the fact that drivers operate under dynamic, nondeterministic, strategic and stochastic environments. Attempts to monitor and analyse driver behaviour are revealed in notable studies including: a study on detection of driver distraction levels due to engagement in secondary tasks while driving by Li, Jain and Busso [19]; a study on driving style analysis using data mining techniques by Constantinescu, Marinoiu and Vladoiu [22] and studies on recognition of driving sub-tasks, maneuvers and routes by Sathyanarayana et al. [20], [21]. Scopes of these studies have been limited by a number of factors, namely: study methodology; vehicle model compatibility; study cost; overestimation of critical driving events; and scope for driver behaviour monitoring. These has seen modern-day studies inclined towards simulator models and the use of pre-existing datasets on driver behaviour. Examples of these models include: a neural car-following model based on naturalistic driving data by Morton, Wheeler and Kochenderfer [13] and a controller design scheme for driver modelling by Wakitani et al. [12]. Probabilistic reasoning and intelligence, which are critical tools in modelling dynamic, nondeterministic, strategic and stochastic environments have been found lacking in the applied methodologies.

1.3 RESEARCH HYPOTHESIS

A utility-based agent can be used as a basis for modelling human vehicle driver behaviour.

1.4 RESEARCH OBJECTIVES

1.4.1 MAIN OBJECTIVE

To model human vehicle driver behaviour using a utility-based agent.

1.4.2 SPECIFIC OBJECTIVES

To achieve the main research objective, the following specific objectives were considered:

1. To identify parameters that describe the behaviour of a human vehicle driver operating under diverse environments.
2. To formulate a vehicle driver behaviour dataset.
3. To develop a vehicle driver agent which can operate in a complex environment.
4. To evaluate the performance of vehicle driver agent.

1.5 RESEARCH QUESTIONS

The following research questions were considered in relation to the objectives:

1. What parameters may be used to objectively describe the behaviour of a human vehicle driver?
2. How can driver behaviour be analysed to formulate a dataset of behavioural patterns?
3. What constitutes an intelligent agent that models a human vehicle driver operating under challenging diverse environment?
4. How can a driver behaviour agent be evaluated for performance measurement?

1.6 ASSUMPTIONS

1. The performance and behaviour of a vehicle driver is influenced by numerous factors including type and state of the vehicle; state and type of the road; environmental conditions; time of day and the state of the driver among other factors. Due to the complex nature of these factors:

    i) The study sample comprised different types of vehicles with different states assumed to be a representative of other vehicle types and states.

    ii) To accommodate the varied states and types of roads, drivers were subject to different road segments with average behaviour established.

    iii) Analysis was not specific on time of day and other environmental conditions during the test i.e. either wet or dry roads, day or night time.

iv) A vehicle validly licensed to operate on Kenyan roads with valid inspection permits is considered to be road worthy, hence mechanically okay.

v) A vehicle driver in possession of a valid driving permit was assumed to be experienced in driving.

vi) The sampled drivers were assumed to be sober i.e. not under that influence of alcohol.

vii) The sampled drivers were assumed to be relaxed with energy and vigour i.e. not exhausted, stressed and/or fatigued.

2. Power supply and internet connection to the GPS server during the testing period would be stable with minimal and/or no downtimes, to ensure that no update from GPS receivers is lost. The server was put on Uninterruptable Power Supply (UPS) to mitigate on any power blackouts not exceeding 15 minutes.

3. The GSM network would be stable and available. A GPS receiver operating in a low GSM network region may fail or delay to relay updates to the server hence compromising on accuracy during analysis. The study attempted to mitigate this challenge by using SIMs from reputable GSM network service providers with a wide stable network coverage.

1.7 LIMITATIONS

1. GPS is provided by the Government of the United States of America (USA) to civilians at performance levels specified in the GPS Standard Positioning Service Performance Standard. GPS signal in space suffer a worst-case pseudorange accuracy of 7.8 meters at a 95% confidence level [23]. The actual accuracy users attain depends on varied factors, including atmospheric effects, sky blockage, and receiver quality. According to the Official USA Government information about GPS [23], real-world data from the Federal Aviation Administration show that high-quality GPS Service Performance Standard receivers provide horizontal accuracy better than 3.5 meters. Furthermore, GPS signal strength is a horizontal dilution of precision (HDOP) value as a measure of the geometric quality of a GPS satellite configuration in the sky. It is a major factor in determination of the relative accuracy of a horizontal position for a GPS receiver. The smaller the dilution of precision (DOP) number, the better the geometry. This study was hence based on the assumptions that:

i) A maximum GPS position radius accuracy of 3.5 meters would be good enough to establish and model driver behaviour. This is based on the maximum expected horizontal accuracy rating of 3.5 meters for high-quality GPS Service Performance Standard receivers [23].

ii) A HDOP value less than 5 would be an indicator of good GPS signal strength per data point received at the server.

2. Real-time tracking in this case is meant to be some few seconds (approximately 3 seconds) behind the normal global time. This is based on the fact that the GPS receiver has to gather then process the data before sending hence some delay in the entire process in addition to network latency aspects.

1.8 SCOPE OF THE STUDY

The study aimed at modelling human vehicle driver behaviour using a utility-based agent. It should be noted that vehicle drivers operate under dynamic, multiagent, stochastic, partially observable, unknown and nondeterministic environments. This poses a complexity challenge in modelling of driver behaviour since not all behavioural parameters are accessible. The study was hence limited to speeding, acceleration, deceleration, stopping and cornering trends. In addition, detection of driver operational environment was limited to detection of road pattern and road terrain.

1.9 SIGNIFICANCE OF THE STUDY

The study contributes towards the efforts of understanding human vehicle driver behaviour and possibly aid in future strategies for minimising if not fully controlling the rate of fatalities. The findings of the study contribute greatly to the society. For instance, information acquired by means of the study is a basis for a knowledge-base on driver behaviour. These could find numerous applications that include: formulation of rules for use in driverless vehicle control systems; establishment of standards of rationality in driving; formulation of policies by road safety stakeholders; vetting of drivers by driver recruiting firms; formulation of road safety and advisory messages among others. The functions of the driver behaviour monitoring model could also be extended to providing advisory services to drivers in real-time. Moreover, the resulting driver behaviour dataset could be used by other researcher in the same area. Finally, the resulting full model provides a data collection and analysis platform that could be used by any interested parties for any kind of study on driver behaviour. These may in turn result to an African context driver behaviour dataset and a data collection and analysis platform.

The outcome of the study is vital to two main categories of beneficiaries: researchers in the same field and other varied categories of stakeholders:

A. Researchers Working in the Same Field of Study

Researchers and scholars in the field of transport and safety could find the dataset as a foundation for their studies. Furthermore, they could find the model for monitoring and determining driver behaviour useful to them in the sense that they could use it to build customized datasets.

B. Different Categories of Stakeholders:

1. Policy makers in the transport sector

   The dataset could be a major basis in the formulations of policies on transport and safety guided by different driver behaviour on the roads. Policy makers could also use the model to gather and determine behaviour on different road segments, regions and vehicle service sector of interest.
2. Insurance companies

   Adoption of the model for monitoring and determining driver behaviour, could assist insurance companies by keeping a log that could be used to ascertain the driving behaviour of insured vehicles.
3. Driver recruiting firms

   Driver recruiting firms could the model to test drivers driving skills before recommending them for recruitment in potential companies or organisations.
4. Road safety stakeholders

   The model will be handy in driver behaviour profiling that could avert on unsafe driving styles if action is taken in good times.
5. Vehicle owners, whether private or public

Vehicle owners could find the model for monitoring and determining driver behaviour useful in the sense that they will be in a position to automatically generate driver behaviour profiles at a click of a button whenever needed for analysis.

6. The general public

   Adoption of the model by all the above stated stakeholders will lead to a general address to National and/or global road safety. Traffic injuries will hence reduce as a result of having drivers with good behaviour on roads. In return, the general public that include other vehicle drivers, pedestrians, passengers among others will be safe on the roads.

1.10 SUMMARY

The chapter introduced the research by discussing the background of the study, problem statement and its justification, the study hypothesis, objectives and research questions, assumptions and limitations, the scope of the study and finally the significance of the study. The next chapter discusses literature on related work with the identification of the research gap.

CHAPTER 2
LITERATURE REVIEW

This chapter explores the state of road safety, factors leading to traffic collisions and previous work on driver behaviour modelling. Contemporary studies on vehicle driver behaviour modelling are discussed under three sub headings, namely, driver behaviour monitoring and profiling, driver assistance and driver modelling. The chapter concludes with a summary of the reviewed literature leading to the identification of the gap.

2.1 ROAD SAFETY AND FACTORS LEADING TO TRAFFIC COLLISIONS

Road users worldwide desire to attain maximum safety as they undertake their day to day activities. It is hence necessary to lay this studies literature review foundation by first exploring the state of global road safety and the factors leading to traffic collisions.

2.1.1 THE STATE OF GLOBAL ROAD SAFETY

Road traffic injuries are estimated to be the eighth leading cause of death globally, with an impact similar to that caused by many communicable diseases [1], [2]. The number of road traffic deaths globally plateaued at 1.2 million annually between the year 2007 and 2013 [3]. In 2016, the number of deaths worryingly hit 1.35 million [2]. However, in years 2015 and 2016, statistics showed that the numbers plateaued or even increased in several member countries of the International Traffic Safety Data and Analysis Group (IRTAD) [24].

Despite the fact that the year 2017 provisional data by IRTAD [24] showed encouraging downward trend, unfortunately, based on data from the last three years: 2014, 2015 and 2016, it is uncertain whether the overall downward trend maintains. Regrettably, the 2018 global status report on road safety [2] by the World Health Organisation ranks traffic injuries as the leading cause of deaths in the younger generation aged between 5 and 29 years. Moreover, 20 – 50 million people end up suffering nonfatal injuries [1]. This is a trigger for a need for a shift in the current child health agenda that has largely neglected road safety [2].

2.1.2 FACTORS CONTRIBUTING TO TRAFFIC COLLISIONS

According to the International Traffic Safety Data and Analysis Group [24], [25], driving under the influence of alcohol, speeding, non-wearing of seat belts and helmets, and the use of mobile phones while driving represents common safety challenges in all countries. Similarly, but with only one different factor, the global status reports on road safety by the World Health Organisation have consistently flagged five key risk factors that require attention by nations intending to address road safety, namely, speeding, driving under the influence of alcohol, nonuse of motorcycle helmets, nonuse of seat belts and nonuse of child restraint systems [1]–[4]. Experience shows that regulation, enforcement and education to modify behaviour on these fronts bring large benefits that lead to shifts in both the behaviour of road users and attitudes towards road safety [1]–[4], [24], [25].

A number of countries, such as Australia, Canada, France, the Netherlands, Sweden and the United Kingdom have achieved steady declines in road traffic death rates through coordinated, multisectoral responses to the problem [1]. These involve implementation of a number of proven measures that address the safety of the road users, vehicles, road environment and post-crash care [1].

The contributory factors to road injuries are many and varied. For instance, according to the road safety strategy 2013 – 2020 report by the Ireland's Road Safety Authority [5], the contributory factors listed by An Garda Siochana on collision report between 2007 and 2011 depict that driver error accounted for 84.8% of all contributory factors identified in fatal collisions. Other factors include pedestrian error, status of the road, environment and vehicle mechanical factors, which accounted for 7.8%, 4.6%, 2.5% and 0.3% respectively. In a separate study carried out in the year 2010, human factors accounted for 74% of road crashes in Tanzania while conditions of vehicles and roads accounted for 12% and 14% respectively [6]. Based on the two independent statistical investigations, it is evident that human factors, that are driver behaviour related emerges to be the major contributory factor to traffic crashes. These factors include careless driving, overspeeding, improper overtaking, overloading, driving under the influence of alcohol, among others. Speeding and driving under the influence of alcohol have consistently been highlighted in World Health Organisation's global status reports on road safety and the

International Traffic Safety Data and Analysis Group's annual reports for member countries [1]–[4], [24], [25].

2.2 PREVIOUS WORK ON VEHICLE DRIVER BEHAVIOUR MODELLING

The process of vehicle driver modelling requires a thorough understanding of the vehicle driver's operational environment, how the driver behaviour can be monitored in realtime and finally the mechanisms that could be used to profile a vehicle driver's behaviour. Additionally, it is worth exploring mechanisms for vehicle driver assistance.

2.2.1 DRIVER BEHAVIOUR MODELLING AND PROFILING

Considerable research on driver behaviour monitoring has been conducted. Some of these studies demonstrated the use of self-reported data, human psychology data, GPS data and CAN-Bus data among others approaches [20], [22], [26]–[31]. Among the first techniques is a 50-itemed Driver Behaviour Questionnaire introduced in 1990 as a seminal article by Reason et al. [29]. Data for 520 drivers collected by the questionnaire was first analysed through a Principal Component Analyses (PCA) with the outcome showing that errors were statistically distinct from violations. This supported the hypothesis that errors and violations were governed by different psychological factors [29]. The questionnaire was at some point recommended by De Winter et al. [28] as a prominent measurement scale for examining driver's self-reported unusual behaviours as a predictor factor. The questionnaire has been used in different studies with some studies revising the scale. reformulating the questions or even adding new questions. Some of these studies include: Zhao et al. [32]; Martinussen, Moller and Prato [33]; Martinussen et al. [34]; Gueho, Granie and Abric [35] and Mattsson [36].

Other approaches for determining driver behaviour used different driver monitoring tools, some of which function as either road-side sensors or on-board sensors. In such scenarios, unaware drivers can be monitored using road-side sensors, where different sensors could be used [27]. The most common sensors in such cases are cameras that could track vehicle trajectories via image processing. Conversely, there is an inclination towards on-board sensors that allow observations under more flexible experimental conditions [27]. On-board sensor come with an added advantage that lies in their possibility of observing manoeuvres of particular interest in a controlled manner.

Several existing studies considered using vehicles equipped with multiple sensors. For instance, the UTDrive, the smart vehicle project is part of an on-going international collaboration between universities in Japan, Italy, Singapore, Turkey and USA whose principal objectives were to collect and research rich multi-modal data recorded in actual car environments for analysing and modelling driver behaviour [17], [18], [21], [37]. According to Angkititrakul et al. [18], the UTDrive, USA project was designed specifically to address five main aspects:

i) Collect rich multi-modal data recorded in an in-vehicle environment
ii) Assess the effect of human–machine interactive system on driver behaviour
iii) Formulate better algorithms to improve robustness of in-vehicle Automatic Speech Recognition (ASR) systems
iv) Design adaptive dialog management which is capable of adjusting itself to support a driver's cognitive capacity
v) Develop a framework for smart inter-vehicle communications.

The UTDrive corpus consists of audio, video, brake or gas pedal pressure, head distance, GPS and CAN-bus data [4], [17], [18], [21], [37]–[40]. Several sensors are incorporated to gather these data [37], [41], including:

i) Five microphone array to capture audio signals inside the vehicle
ii) Two firewire cameras to capture driver's face region and front-view of the vehicle
iii) 16 points J1962 for recording CAN signals from the On-Board Diagnostics (OBD)-II port
iv) Brake and gas pressure sensors
v) Distance sensors
vi) GPS receivers
vii) Hands-free car kit, biometrics for heart-rate and blood pressure measurement
viii) A fully integrated data acquisition unit.

A proposal by Yu and Hansen [42] for an enhancement to the voice activity detection, presented a novel and robust performance against various in-vehicle noisy scenarios from the UTDrive project. Rather than computationally extracting the speech features, the information of in-vehicle spatial power distribution is employed. This acts as the discriminative feature for speech activity decision with a pre-fixed endfire Minimal Variance Distortionless Response (MVDR) beamformer designed simultaneously as speech enhancers and spatial power estimators for driver's position and a fixed noise sensing beamformer is also designed serving as power estimator from other positions [42]. The strengths of the proposed voice activity detection system include: high integration with speech enhancement algorithm used by the UTDrive; great computational efficiency; ability to avoid speech feature extraction; use of only two pre-fixed beamformers and pre-trained GMM classifier. The solution provides robust and novel performance for various in-vehicle noisy scenarios, such as the impulse (bumper) noise, automotive audio music, and engine noise.

The UTDrive project is a major development in the study of vehicle driver behaviour with an inclination to an in-vehicle environment i.e. detection of driver distraction. It is worth noting that a distraction of any magnitude in the attention of drivers can lead to disastrous consequences. Hence, notable studies on driver behaviour and performance with respect to involvement in in-vehicle secondary tasks have been conducted [19], [21], [38], [43]. Secondary tasks in this case refer to separate tasks done during driving including, operating a cell phone, radio or GPS navigational systems. Some of these studies used the UTDrive platform for data collection. One such a study was conducted by Li, Jain and Busso [19] using non-invasive sensors to capture audio, video and CAN-Bus features in real-traffic situations. The study was based on the UTDrive platform to build a dataset from 20 drivers. The data was collected in a real-driving scenarios, where the drivers were asked to perform common secondary tasks such as operating the radio, phone and a navigation system while driving [19]. Data processing used Feature Analysis techniques: K-Nearest Neighbour (KNN); Linear Regression and Second order polynomial kernels; Sequential Floating Forward Selection (SFFS) for data analysis. The study proposed the Gaussian Mixture Models (GMMs) to capture the complex distribution of multimodal data to estimate the distraction level [19].

Li, Jain and Busso [19] determined the mean of the log likelihood ratio across the normal and seven task conditions. The approach achieved promising results suggesting that it is possible to measure the distraction level of drivers. It was observed that certain tasks are more distracting than others. For instance, GPS following and conversation induce driving behaviour that is closer to the expected normal [19]. Other secondary tasks such as operating radio, using phones, operating GPS, and taking or watching pictures while driving results to the most deviation from normal behaviour [19]. The prediction of the proposed model strongly correlated with subjective evaluations describing distractions [19]. The study was limited to corpus recording on a predefined route on urban roadways with specific speed limits and traffic signals. Furthermore, drivers were required to perform secondary tasks in sequential order. Such restrictions are likely to yield results that do not fully reflect normal behaviour since behaviour changes under different environmental conditions.

A more or less similar study by Jain and Busso [43] had earlier on been carried out aimed at observing driver behaviour while performing in-vehicle common tasks that could affect their attention. The UTDrive platform was also employed in the study, just like in the later study by Li, Jain and Busso [19]. The aim of the study was to identify relevant features extracted from a frontal video camera and the car's CAN-Bus data that could be used to distinguish between normal and task driving behaviour. Study findings show that data obtained from a frontal video camera is useful in distinguishing between normal and task conditions. This is best achieved by analysis of the mean of the driver's head yaw motion. According to Jain and Busso [43] with respect to the study objectives, the features from the CAN-Bus data provided a small but significant improvement on study results. For instance, CAN-Bus data slightly degraded performance with respect to GPS operating and phone talking. Results indicated that driving style was preserved during performance of the two tasks. The features are however useful for operating radio, following GPS, operating phone and engaging in a conversation. Conclusively [43], analyses from both frontal video camera and CAN-Bus data gives complementary information that can be potentially used to track the attention levels of a driver. The study was limited to an in-vehicle environment with a major focus on frontal video camera data supplemented by CAN-Bus data.

Using vehicle speed, steering wheel angle and brake force as the only vehicle CAN-Bus signals, Sathyanarayana, Boyraz and Hansen [20] recognised three different vehicle maneuvers, namely, left turn, right turn and lane change. The raw data used in the investigation represented a small portion of the UTDrive corpus for the years 2006 and 2007 on a real-road experiments. The study applied the Hidden Markov Model towards modelling driver behaviour and route recognition. The major contributions of the study are: first, it proposes a hierarchical way of formulating the maneuvers and combining them for the route models and second, it proposes a plausible solution to maneuver recognition and driver distraction detection problems. In an extensional study Sathyanarayana et al. [21] included detection of sub-tasks involvement by drivers while driving. This came as a further behavioural element monitored in addition to maneuvers and route recognition. To effectively detect distractions, the study used the Gaussian Mixture Models (GMM). The findings of the study show that CAN-bus signal analysis performed for longer-term time-windows give an opportunity for the development of human-centric systems capable of recognising the context or maneuver and detecting driver distraction or abnormalities [21]. It is worth noting that CAN-Bus data annotates GPS data by providing exhaustive information about the dynamic state of the vehicle. Regrettably, to date, CAN-Bus data is not available in the same quantity as GPS data, and is further not documented by most car manufacturers [30]. This is hence a major limitation to studies that opt to incorporate such data. Moreover, the high monetary costs involved in such approaches results in smaller sample sizes hence limiting on study objectives and scopes [26].

A risk index framework and methodology for describing drivers by risky behaviour using a composite driver risk profile was proposed by Ellison, Greaves and Daniels [26]. The study started with a demographic and personality survey for participating drivers followed by 25 consecutive days of GPS data collection in instrumented vehicles with drivers unaware that their speeds were being monitored [26]. Mobile Devices Ingenierie C4 GPS devices were used to collect 8 million second-by-second driving speeds, locations, date and time from 106 drivers in Sydney over several weeks. Due to limitations on the availability of data on behaviours such as distraction, fatigue and driving under the influence of alcohol, the analysis relied on vehicle speed beyond speed limits and acceleration as key risky behaviour measures. The analyses used correlation of variance in speed, acceleration and braking behaviour for driver profiling [26]. The findings of the study showed that over 90 percent of drivers exhibit more variability in speeding, acceleration and braking behaviour between different road environments than within the same road environment. It is worth noting that a segment of drivers will always be prone to extremes in risky behaviour. Ellison, Greaves and Daniels [26], hence, confirms behaviour variability between spatial-temporal contexts to be high among many drivers than within the same spatial-temporal context. Conclusively, it is possible to accurately develop effective road safety messages through examination of profiles for drivers who engage in behaviours of interest [26]. This analysis points to the potential for using more disaggregate data but also the indicates the necessity for controlling the temporal and spatial factors when studying driver behaviour.

GPS devices have the capability of collecting much more disaggregate data from drivers when used as on-board sensors to monitor driver behaviour [26]. For instance, Constantinescu, Marinoiu and Vladoiu [22] surveyed driving styles for aggressiveness, speed, acceleration and braking using GPS position, time and speed values collected at one second interval. Data for 23 different drivers was collected under two controlled test drives, over 2 to 5 working days and in similar conditions at the Bucharest city. The study used multivariate analysis techniques: Hierarchical Cluster Analysis (HCA) and PCA to identify and explain drivers grouping according to their driving behaviour. Using two principal components (PC1, PC2) and three rotated components (RC1, RC2, RC3), four driver behaviour clusters were established, namely, aggressiveness, speeding, acceleration and braking [22]. Different driving styles were determined per cluster, subjected on a Likert kind of measurement scale. The scale rated the clusters as either very-low, moderately-low, neutral, moderately-high or high. It was observed that many other factors affect driver behaviour, for instance, driver fatigue, driving environment, traffic context, driver’s individual characteristics among others [22]. Unfortunately, as a major limitation, data to generate all this information could not be accessed for their set of drivers.

A classification of the dissimilarity of the longitudinal driving behaviour was investigated by Lu et al. [44] in China. The study used a simulator with 24 test drives for experimentation purposes. According to Lu et al. [44], driving behaviour could be characterized using measurable safety parameters related to time headway (THW), time-to-collision (TTC), elapsed time (from lead vehicle deceleration start to brake activation, and from lead vehicle deceleration start to accelerator pedal release), TTCi (at the brake activation response to the lead vehicle deceleration, and at the accelerator pedal release to the lead vehicle deceleration) and switch time (from accelerator pedal release to brake activation). The study used host vehicle state and laser radar data for both lead vehicle and car-following data collection scenarios. The K-means clustering algorithm was employed to partition the collected data into some form of clusters. The findings from the study show that the dissimilarity in longitudinal driving behaviour can be classified as four driver groups using measurable safety parameters, namely, prudence, stability, safety-mindness and skillfulness. Each of the four can be viewed in a paired perspective signifying the best case or worst case scenarios, where:

i) Prudence - aggressive verses prudent
ii) Stability - unstable verses stable
iii) Safety-mindness - risk prone verses safety prone
iv) Skillfulness - non-skillful verses skillful

Lu et al. [44] study findings show that prudent drivers prefers higher switch time from accelerator pedal release to brake activation to give them more time to estimate danger states. It however, comes out clearly that it is difficult to estimate a driver’s skill level [44]. The study thus used a supposition that non-skillful drivers have smaller elapsed time from leading vehicle deceleration start to accelerator pedal release. The results show that the K-means algorithm is an efficient and simple for clustering applicable is similar study area. The main limitation was that the study was simulator-based, hence, real world application remains unknown. In their conclusion, Lu et al. [44] alludes that more experiments would be done in the simulator, and the classified results of driver characteristics would be further evaluated by real world experiments, comparative analysis would be carried out of the differences of the driving behaviour in the driving simulator and the real world environment in future work.

A slightly similar study was later carried out by Bifulco et al. [27] to investigate whether driver behaviour either in active or passive modes induces different driver performance. Active mode is where on-board sensors are used to obtain measures relative to the vehicle ahead hence the driver being observed is in the instrumented vehicle. In this case, the car-following process is defined with respect to the vehicle ahead. On the other hand, passive mode is where the leader is the instrumented vehicle and the observed driver is the vehicle behind, most probably unaware. The study [27] considered vehicle speed, the adopted headway and time-to-collision. Study findings show that driving speeds are not dispersed across drivers and along the road stretches concerned. Additionally, they are similar both in average and deviation for active and passive observations. More heterogeneity between drivers is observed with respect to the headway the drivers adopt, which is lower in passive mode. The analysis showed if H threshold is 2 seconds, more than 80% of the time, potentially dangerous conditions are found, while a H threshold around 1 second leads to safety conditions for about 50% of the drivers. The safety condition seems to be independent of the chosen time to collision threshold. Observations in passive mode exhibit slightly more dangerous behaviour. Driving behaviour during car following were investigated to verify whether active and passive experimental conditions induce different driver performance where the tests concerned the mean speed and mean headway of each clip. The resulting samples were found not to be normally distributed. Equal speeds for active and passive observation were expected, given that overtaking was not allowed on the study route. However, an influence of the observation technique was evidenced whereby drivers unaware of taking part in the experiment tended to maintain a lower headway with respect to the active drivers [27]. The study was limited to a specific region: a 78 km tour with each driving session lasting about an hour on a route consisting of a single loop with overtaking prohibited.

The use of smartphones as a cheap, easy-to-deploy with numerous sensors for driver monitoring can be witnessed in a number of recent experiments [7], [39], [45]–[47]. For instance, Johnson and Trivedi [7] proposed a method for determining both driving style and type of driving maneuver using sensor fusion and the Dynamic Time Warping (DTW) algorithm. The study [7] was a complete driver monitoring system on an iPhone 4 that recorded and played back video and sensor data in a sychronised manner. The study compared individual sensor data versus sensor-fused data for driving event recognition. Johnson and Trivedi [7] conclude that the combination of x-axis rotation rate, y-axis acceleration and pitch are the signals best suited for use with the classical DTW algorithm. Additionally, the DTW algorithm can accurately detect events with a very limited training set. Johnson and Trivedi [7] proposed solution serves as a novel research tool that can be easily and inexpensively distributed to a wide audience due to the ubiquitous nature of smartphones. The system actively detects and records events that characterise a driver’s driving styles, thus, increasing the awareness of potentially-aggressive actions, and further promoting driver safety. The findings of the study show that sensors available in smartphones can detect movement with similar quality to a vehicle CAN-bus hence making it a viable and inexpensive monitoring utility. A major limitation with the usage of smartphones is detection of noisy signals, which affects accuracy and reliability [7], [46]. Another notable challenge is the fact that mobile measurements tend to overestimate critical driving events [39]. This is possibly as a result of deviations from the initial calibrated position with respect to the relevant vehicle axes [39].

DriveSafe is a driver safety application for iPhones that detects inattentive driving behaviour, provides feedback to drivers, scoring their driving and alerting them for unsafe behaviour [40]. The model highly advocated for the use of smartphones as a cheaper cost option compared to black-box on-board units for driver behaviour monitoring and profiling [40]. The high market penetration [48] of smartphones coupled with numerous sensors [46] is emerging as a cost-effective means for capturing and processing of data from the real world. For instance, DriveSafe model is centered on a smartphone application [40] that requires the driver's iPhone 5 to be placed on the windshield, just below the rearview mirror and aligned with the relevant axes of the vehicle as a calibration mechanism. The application relies on inbuilt iPhone sensors for computer vision and pattern recognition techniques to detect the most commonly occurring inattentive driving behaviours. It detects two main categories of behaviour i.e. drowsiness and distractions [40] where,:

i) Drowsiness is inferred based on lane weaving and drifting behaviours using rear cameras, microphone and GPS sensors. In this case, lane weaving is detected if a driver changes lanes without turning the blinkers, while lane drifting is detected in cases where the driver fails to keep the vehicle within the center of the lane.
ii) Distractions are evaluated based on sudden longitudinal shifts indicated through acceleration, braking and turning events.

These measurements are facilitated by the use of GPS, accelerometer and gyroscope iPhone sensors. Under normal circumstances, the accelerometer provides data in the range of -1 to 1 while the gyroscope data ranges between $-180°$ to $180°$ [49]. Actual event detection depends on pre-processing of detected parameter that involves different mathematical functions and algorithms. The application then scores the driving behaviour based on the frequency and intensity of event detections with alerts presented to the driver on a Graphical User Interface (GUI) [40]. An alarm is triggered if certain thresholds are exceeded.

The DriveSafe application's evaluation in detection of inattentive driving behaviour obtained an overall precision of 82% at 92% of recall. A comparative analysis with the commercial AXA Drive application showed the DriveSafe application portraying a better evaluation based on its operation [40]. The major limitation is the fact that the application only detects events at velocities higher than 50 km/h [40], [48]. Furthermore, the application majorly focuses on detection of drowsiness and distractions as opposed to the nature of operational environment. Further plans by Bergasa et al. [40] are geared toward adding new functionalities, for instance, forward collision warnings with other vehicles and to have the new version of the application available on Apple store for download and use by interested parties. To further improve on event detection and scoring capabilities, machine learning techniques will be a future consideration for inclusion.

A more recent study by Arroyo, Bergasa, and Romera [48] presented an adaptive fuzzy classifier for identification of sudden driving events based on acceleration, steering and braking styles using smartphones. The study used inertial and GPS smartphone in-built sensors for detection of driver behavioural parameters. Just like in the case of Bergasa et al. [40] and Eren, Makinist and Akin [49], the model by Arroyo, Bergasa, and Romera [48] detects acceleration and braking events based on sudden longitudinal changes measured by the accelerometer. The model is composed of a fuzzy classifier that classifies events as acceleration, braking, steering and bumps centered on fuzzy logic and fuzzy rules without basing on fixed thresholds. As part of study findings, a comparative experimentation of the DriveSafe by Bergara et al. [40] and the adaptive fuzzy model saw the fuzzy model significantly reduce the number of false detections with considerable increase in real detections. This was attributed to the fact that the model adjusts fuzzy classifier decision thresholds using data obtained in certain routes as opposed to the use of fixed thresholds. Furthermore, the fuzzy classifier model at velocities lower than 50km/h, which came as a major improvement on the DriveSafe model's detection threshold. The fuzzy model has an added capability of detecting changes in road quality with respect to bumping or irregularities of the asphalt. Additionally, the model is currently limited to detection of sudden driving events with respect to acceleration, steering and braking. In future, Arroyo, Bergasa, and

Romera [48] intend to make the model to detect new events like overtaking attempts, abrupt gear shifts or sudden swerves as a way to enhance on driver behaviour detection.

An evaluation study of driver profiling fuzzy algorithms using GPS, accelerometer, magnetometer and gravity smartphone sensor had early been carried out by Castignani, Frank and Engel [46]. The proposed model puts all event types at the same scoring priority level merged in a global event counter. Sensor data from the smartphone is first filtered with events detected for the different metrics. This is followed by input data fuzzification with fuzzy rules applied in a Fuzzy Inference Engine. Finally, a score is produced through a defuzzification process ranging from 0 to 100. A survey involving 20 drivers in different trips showed that drivers mainly belong to moderate and aggressive categories [46]. The study used a passive mode, where drivers involved were unaware that they were being monitored. In future, Castignani, Frank and Engel [46] aim to validate the accuracy of the obtained scores by involving the same drivers who will have been informed about their score from the first experiment. The focus of the second experiment would be on the analysis of driving behaviour changes, since all drivers will tend to drive more efficiently in order to reduce their scores.

Along similar lines of adaptive fuzzy logic for driver profiling, Castignani, Derrmann, Frank and Engel [50] proposed SenseFleet, a platform for driving event detection and scoring. The event detection algorithm used in SenseFleet uses accelerometer, gravity, magnetic and GPS smartphone sensors [50]. The model uses fuzzy logic to detect acceleration, braking and steering events [50] from sensor data. These events are then combined with weather information and time-of-day through a scoring function for better determination of a score based on risky behaviour [50]. In order to detect events independently of the mobile device and different vehicle conditions, an initial calibration phase was done to establish the boundaries of the fuzzy membership functions for input variables. Using SenseFleet's mobile application or a web-based dashboard user interface, the overall score for all the trips and the relative distribution of event types can be analysed [50]. Each time an event is detected, a sound and text notification is triggered by the application as an instantaneous alert to the driver [50]. The platform was validated through an evaluation study considering multiple drivers along a predefined path. The findings showed that the platform was able to accurately detect risky driving events and provide a representative score for each individual driver. The model is able to distinguish between aggressive and calm drivers. A comparison of scoring results with subjective risk metric provided by each individual driver for their experiments showed that SenseFleet scores were equivalent to individual drivers' feedback in around 90% of the cases within + or - 1 neighbouring driver clusters. The study was however limited to a predefined test environment with a whole phase dedicated to sensor and vehicle calibration. Calibration stands out to be the norm for studies using smartphone sensors for data collection. Castignani, Derrmann, Frank and Engel [50] future work aims at the analysis of the impact of calibration on the event detection and the evaluation of different approaches for the fuzzy sets definition, considering other types of membership functions and statistical analysis over calibration data.

It is worth pointing out that the use of smartphones' inertial sensors to detect driver behavioural parameters features in three major reviewed models, namely, the DriveSafe model by Bergasa et al. [40], the fuzzy model by Arroyo, Bergasa, and Romera [48] and the SenseFleet model by Castignani, Derrmann, Frank and Engel [50]. Smartphone sensors face a number of challenges, two of which could have a great impact on the accuracy of the measurements [48]: first, the diversity of the inertial sensors where measurements and noise level can differ among different devices and second, smartphones position with respect to the relevant axis of the vehicle is critical as a form of calibration. Castignani, Derrmann, Frank and Engel [50] notes that different smartphones embed different sensor chipsets that have different sampling rates and magnitudes. Thus, it is necessary to calibrate smartphone-based systems to each particular vehicle and device. Hence, most modern day experiments [40], [49] for detecting driving events using inertial sensors are based on fixed thresholds to determine whether to report the event or regard it as noise. Accurate calibration is therefore required to establish these thresholds. Consequently, researchers still base their experiments on both the use of on-board units and smartphones with no major bias on either of the two.

2.2.2 DRIVER ASSISTANCE

Vehicular Ad-hoc Networks (VANETs) are a subclass of Mobile Ad-hoc Networks (MANETs) in which automobiles act as mobile nodes capable of communicating with one another, creating a mobile network within a wide range [10], [51]–[53]. Such networks are based on wireless interface devices that allows them to communicate using short range communication systems called Dedicated Short Range Communication (DSRC) [52], [53]. Unfortunately, practical implementations of VANETs is still a costly adventure. This is majorly due to the sophisticated infrastructure required to setup VANETs.

VANETs form the basis upon which a moving vehicle can be able to gather, process and disseminate information both for safety and non-safety related goals on the road. VANETs represent two main categories of communication: Vehicle-to-Vehicle (V2V) and Vehicle with Infrastructure (V2I) communication [51], [53], [54]. In the Vehicle-to-Vehicle model, information exchange occurs amongst vehicles whereas in the Vehicle-to-Infrastructure model, traffic information is collected at the Road Side Unit (RSU) and then broadcast to the receiver vehicles and finally transmitted to a central server for vehicle monitoring [53]. Vehicles-to-Roadside communication (VRC) is a hybrid architecture of V2I and V2V, where the wireless networking devices are fixed in roadside communication units such as cellular towers, access points and vehicles to facilitate communication by exchanging information received from vehicles or infrastructure equipment via ad hoc communication [55]. These communication uses a Dedicated Short Range Communication Protocol (DSRC) in a bidirectional manner. A more or less similar hybrid DSRC cellular architecture for V2X communications in urban scenario is presented in a study by Abboud, Omar, and Zhuang [56].

Applications supported by VANET can be grouped into two major classes, namely: safety-oriented and non-safety-oriented applications [10], [54], [55]. Safety-oriented applications [10], use-cases include intersection collision alerts, lane change assistance, overtaking alerts, head on collision alerts, cooperative forward collision alerts, emerging vehicle warnings, cooperative merging assistance and collision risk alerts. On the other hand, non-safety-oriented applications [10] aim at providing both drivers and on-board passengers with streaming media and Points of Interest (POIs) such as gas stations, nearest parking lots, restaurants, hotels, shopping malls, fast food, among others. Such Points of Interest may be presented in form of marketing adverts to on-board passenger via VANET enabled vehicles [10]. However, practical implementation of VANETs face a number of challenges that include highly dynamic topologies, mobility modelling, signal attenuation and hard delay constraints among others [55].

A model for driver assistance is proposed by Martin-Fernández and Caballero-Gil [54] as a practical and low-cost implementation of VANETs using only smartphones. The study [54] describes a hybrid network architecture, which allows V2V communication, either directly or through the cloud with an android mobile application alerting drivers through sound messages regarding events happening near them. The application is able to detect a number of events that include: collisions between vehicles by measuring changes between gyroscopes and accelerometers, the G-Force on the smartphone; detection of heavy traffic by monitoring speed changes as a sign of possible congestion; detection of road signs using preloaded data on road signs; release of a parking space by detection of when a vehicle is started and is leaving the space where it was parked [54]. Simulation results for the proposed system portrayed promising results. Deployment of the proposed model in a real environment whose results are unknown is the next research goal [54]. The study was purely limited to the use of smartphones which require thorough calibration. Smartphones are also prone to overestimation of measurements and noisy detections.

In the same line of Intelligent Transportation Systems, Joshi, Singh, and Moitra [53] presents an algorithm based lane changing model centered on vehicle speeds and GPS data in form of a VANET. The study used a road with five different lanes with the speed limit increasing from the left most lanes to the right most one i.e. 0 – 40 km/h (stop), 41 – 80 km/h, 81 – 119 km/h, above 120 km/h lanes [53]. Vehicles have to move according to predefined lane speed limits with permissions to increase or decrease their speed but change lanes only when the minimum gap between the vehicle and its leading vehicle is as defined in the algorithm [53]. The information received about GPS coordinates and velocity is parsed to check the current position of the vehicle with respect to the lane and lane speed limit [53]. In case the driver violates rules, the on-board unit in the vehicle displays an LCD warning message with an audible warning tone to the driver to either change lane or speed [53]. Failure to react to a number of warnings, the message is broadcast to other vehicles and the RSU’s within the communication range of vehicle [53].

This is later followed by the RSU escalating the message to the nearest traffic monitoring system as a traffic offence requiring action [53].

Fernandez and Ito [9] proposed a driver behaviour model comprising a knowledge base and a reasoning module. The knowledge base was divided into two parts: The ontological and the rule base modules [9]. The rule base contained the rules to be followed to carry out the different driving task based on driver's percepts and the knowledge in the knowledge base. On the other hand, the ontological module was composed of two sets of information: driver behaviour set and driver environment set [9]. The driver behaviour set contained knowledge associated to driver characteristics, perception and cognitive state towards attention to varied driving tasks [9]. Conversely, the driver environment set held knowledge on the driver's environment, including other vehicles, states and nature of roads, traffic signs, and weather conditions among others [9]. In the model [9], the reasoning module chose the rules to apply to perform the current driving task based on the specific goal and input data from the knowledge base. For better processing, a task hierarchy was maintained in which each driving task was split into subtasks with the Pellet reasoner (an ontology reasoning tool) used to execute the rules that in return produced output in form of actions [9]. Practical implementation of Fernandez and Ito's [9] driver behaviour ontology allows predicting different undesirable situations, such as traffic accidents, and road congestion. Enhancing such predictions with alerts and warning notifications to drivers in real-time can greatly yield positive impact on road safety.

Prioritized and timely transmission of warning messages for safety applications is crucial in VANETs to warn drivers beforehand hence prevent fatal accidents [53]. Singh and Bhasin [51] explore the use of Variable Speed Limits (VSL) whose structure entails implementation of various sensors (loop-detectors) situated along the road, partitioning the expressway into several monitoring segments. Analysis of sensor information determines the speed-limit based on the volume, occupancy and average speed of vehicles within the given segment. The speed limit is then displayed on Variable Message Signs (VMSs) positioned along the roads [51]. To account for different vehicle categories, the VSL model [51] employed Dynamic Speed Limit (DSL) as opposed to the traditional Uniform Speed Limits (USL). The model [51] used VANET technology for propagation of information with sets of RSUs used as loop detectors. Implementation of such a mechanism could help assist drivers to know the speed limits to observe per given road segment hence optimize traffic flow, road safety and travel time with respect to Intelligent Transportation Systems. The major limitation of such a model is the fact that the driver has to keep observing the speed limits displayed on VMSs along the road.

Bumps or speed breakers are safety elements on roads aimed at controlling overspeeding. However, there existence on the road adds up to the complexity of the driver's environment. This is because recognition of bumps is sometime a challenge to drivers especially if not designed in a standard way. Devapriya and Babu [57] presented a novel effortless and simple to implement method for detection of bumps. The methodology involved image processing with alerts to drivers before they get to the exact bump [57]. The complete process for bump detection involves five main steps: Get input image; perform preprocessing; perform structural operation; compute projections and finally bump detection [57]. The methodology is only applicable to bumps designed in a standard way. It is suitable for bumps designed with zebra crossing patterns with an accuracy rate of 84.5% since image processing is centered on the zebra crossing lines [57]. Poorly designed bumps will result to failures in detection. Other limitations lie in the fact that bumps cannot be detected at night and that the image processing approach used cannot distinguish zebra crossing points from bumps.

Considering reviewed contemporary studies on driver assistance, it emerges that some of the driver assistance methodologies still require the driver to keep observing road signs like speed limits displayed on VMSs along the road. Furthermore, some approaches can only be applicable at daytime. For instance, the bump detection model could not be used at night. These and many more factors indicate the fact that there is still need for a real-time driver advisory model that could cater for either desirable or undesirable situations or both. The model should be operational both at daytime and nighttime. It should further try to reduce if not completely stop the number of times the driver has to keep observing road signs for action.

2.2.3 DRIVER MODELLING

There have been a significant number of studies involving simulator models in the attempt to model driver behavior. For instance, a controller design scheme that can be utilised as a driver model in a vehicle simulator is discussed by Wakitani et al [12]. In the proposed driver model [12], the observable information such as vehicle driver actions, driver operation, and environmental condition is stored in the database. The driver's actions such as stepping on the accelerator or brake pedal must be performed in short terms. Thus, any driver model should have a decision-making mechanism that can quickly decide the operation to be performed. The proposed [12] model has a controller acting as a driver's decision mechanism because its action structure is similar to humans. The only limitation of the study lies in the fact that it was purely a simulator model. It is worth noting that simulation allows for testing a wide range of scenarios within a short time span, minimal cost and less or no risk of injury [13], [14]. They however must employ accurate behaviour models for traffic participants in order to produce useful evaluation metrics [13]. Such simulation approaches must ensure that the simulated behaviour is a representative of actual driving, otherwise it may lead to overestimation or underestimation of critical aspects of the safety systems.

Morton, Wheeler and Kochenderfer [13] describes neural car-following models developed based on naturalistic driving data and outlines a general methodology for constructing such models. According to Morton, Wheeler and Kochenderfer [13], human driving models produce distributions over actions rather than maximum likelihood predictions, allowing for stochastic predictions and the evaluation of statistical risks. The study demonstrated the effectiveness of Gaussian mixture networks over the piecewise uniform networks. However, study experiments were limited to the Next Generation Simulation (NGSIM) dataset for Interstate 80, containing 15 minutes of vehicle trajectory data collected using synchronised digital video cameras providing the vehicle lane positions and velocities in the lane relative frame [13].

Along the same lines, a driver model for predicting a vehicle driver's steering wheel angle for collision avoidance maneuvers without prior knowledge of collision avoidance data was proposed by [14]. The model [14] includes a compensatory transfer function, an anticipatory feedforward transfer function, and a method of determining the driver's desired path. The study was also limited to use of data collected by a 10-degree of freedom (DOF) vehicle model, which is a semi immersive virtual environment driving simulator. The study [14] used the MATLAB Global Optimization Toolbox functions for various analysis.

The use of preexisting datasets and or collection of data using prebuild vehicle models comes out as one of the approaches used by modern-day researchers. Ramanishka, Chen, Misu, and Saenko [58], outlines a comparison of various driving scene datasets that could be adopted in any study. These includes Princeton DeepDriving, KITTI, BDD-Nexar, Udacity, comma.ai, Brain4Car and their dataset. The major limitation on the use of such datasets lies in the fact that the dataset limits the study scope to specific regions and on specific parameters available in the set.

Using a different approach rather than the use of simulators and datasets, Noh et al. [15], proposed a highly automated driver agent that allows the driver to take over vehicle control within a certain time constraint when the system requests it. If a take-over request is denied, then the system stops or pulls the car safely off the road. Noh et al. [15], refer to the model as a Co-Pilot, since it acts like a copilot of an airplane helping or replacing the pilot. The system can determine varied driver behaviour and generate trajectories for various driving situations [15]. The approach could be limited by the cost of implementation as it controls actual mechanical effectors.

In conclusion, vehicle driver automation levels can be divided into five categories, namely, human driver only, assisted, partially automated, highly automated, or fully autonomous. Implementation of fully autonomous level is limited by numerous factors. For instance, the current state of art technologies fails to guarantee the performance of localisation, object recognition and decision-making for all possible and complicated road environments [15]. Furthermore, the lack of well-defined rules or laws for self-driving cars on real roads is another limiting factor [15]. These and other factors have led to lots of research focusing on simulator models and driver agents that operate simultaneously with the human driver as assisted, partially automated or highly automated levels. Hence, this study proposes a software driver agent model that offers dashboard display of actions to be undertaken without controlling mechanical effectors. This falls under the assisted level of driver automation. Future advances in technology and infrastructure and enforcement of self-driving car rules could see the model being enhanced to control a real vehicle at a highly automated or fully autonomous level.

2.3 THE IDENTIFIED GAP

From the review of literature, it was noted that many factors affect the bevahiour of a vehicle driver. It is evident that human factors, that are driver behaviour related emerges to be the major contributory factor to traffic crashes. These factors include but are not limited to careless driving, overspeeding, improper overtaking, overloading, driving under the influence of alcohol, among others.

A number of factors limited scopes of reviewed studies, namely: study methodology; vehicle model compatibility; study cost; overestimation of critical driving events; and scope for driver behaviour monitoring. These has seen modern-day studies inclined towards simulator models and the use of pre-existing datasets on driver behaviour. Probabilistic reasoning and intelligence in study methodologies could address some of these deficiencies. Thus, leading to formation of an African context driver behaviour dataset and a data collection and analysis platform. It is hence essential for this study to target an innovative solution that could lead to effective monitoring, analysis and modelling of vehicle driver behaviour.

Table 2.1 outlines a summary of five models on driver behaviour that heavily informed the identification of the gap for this study. These models are part of the studies reviewed in this chapter. The models were proposed by Sathyanarayana, Boyraz and Hansen [20], Sathyanarayana et al. [21], Li, Jain and Busso [19], Morton, Wheeler and Kochenderfer [13] and Wakitani et al. [12].

Table 2.1. Summary of Major Reviewed Models Leading to the Gap

	Sathyanarayana et al. (2009 & 2010) Model	**Li et al. (2013) Model**	**Morton et al. (2017) Model**	**Wakitani et al. (2018) Model**
Description	Recognition of driving sub-tasks, maneuvers (left turn, right turn and lane change) and routes.	Detection of driver distraction levels due to engagement in secondary tasks while driving.	A neural car-following model developed based on naturalistic driving data.	A controller design scheme for driver modelling.
Data Collection	UTDrive platform complemented by CAN Bus data	UTDrive platform	Simulator Model: Next Generation simulation data	Simulator Model
Data Analysis	▪ Hidden Markov Model (HMM) ▪ First Fourier Transforms (FFT) ▪ Gaussian Mixture Models (GMMs)	▪ Feature Analysis: KNN, Linear Regression, Second order polynomial kernels and Sequential Floating Forward Selection (SFFS) ▪ Gaussian Mixture Models (GMMs)	▪ Gaussian Mixture Networks	▪ Data-Driven Control methodologies. ▪ Fictitious Reference Iterative Tuning (FRIT)
Major Findings	▪ A proposed hierarchical way of formulating maneuvers and combining them for route models and a plausible solution to maneuver recognition and driver distraction detection problems. ▪ Detection of sub-tasks involvement by drivers while driving.	▪ Certain tasks are more distracting than others. ▪ GPS following and conversation induce driving behaviour that is closer to the expected normal. ▪ Operating radio, using phones, operating GPS, and taking or watching pictures while driving results to the most deviation from normal behaviour	▪ Human driving models produce distributions over actions rather than maximum likelihood predictions, allowing for stochastic predictions and the evaluation of statistical risks. ▪ The study demonstrated the effectiveness of Gaussian mixture networks over the piecewise uniform networks.	▪ Simulator results showed the model gaining good control in terms of performance for about 10000 steps.
Limitations lead to the Gap	▪ CAN Bus data is expensive. ▪ Studies limited to maneuvers and destructions based on sub-tasks.	▪ Predefined route with specific conditions. ▪ Drivers perform secondary tasks in sequential order.	▪ Purely a simulator model. ▪ Simulated behaviour may not be a representative of actual behaviour.	▪ Purely a simulator model. ▪ Simulated behaviour may not be a representative of actual behaviour.

2.4 SUMMARY

The chapter discussed related modern day literature under three main categories, namely, the state of road safety and factors leading to traffic collisions and previous work on vehicle driver behaviour modelling. It concluded with a summary of the literature review and the identification of the research gap. The next chapter focuses on the proposed model and the methodology for realizing it.

CHAPTER 3
METHODOLOGY

This chapter discusses the methods used to carry out the study. It is organized in a number of sections each focusing on a specific aspect of the methodology. The chapter outlines the research design, study locality, logistical and ethical considerations, theoretical framework, conceptual framework, system model and the data collection and analysis process. The design and development of data collection tools and critical data collection and analysis algorithms are among the key elements discussed in line with the study objectives.

3.1 RESEARCH DESIGN

The study used experimental design as a confirmatory kind of approach. Experiments were designed based on a model that allowed for varying of variables in a manner that could lead to accuracy in the research finding. The choice of real experimental design as the research design for this study aimed at overcoming the recent trend where it was observed that modern day studies on driver behaviour had shown an incline towards the use of datasets and simulators. Unfortunately, simulated behaviour may not be a representative of actual behaviour. Furthermore, as part of the study outcome, a driver behaviour dataset was to be formulated and an agent developed and evaluated, it was critical to use real experiments to accomplish this.

3.2 LOCATION OF THE STUDY

The study was based in several Counties in Kenya. The choice of counties was as a result of the test road segments. Data was collected on the Nairobi – Nakuru Highway, Southern Bypass, Waiyaki Way, Magadi road and Masai Lodge road. The roads were chosen as a representation of three categories of roads in Kenya i.e. dual carriageways, single carriageways and highways. In this case, Nairobi – Nakuru Highway represented the highways category, Southern Bypass and Waiyaki Way represented the dual carriageways while Magadi road and Masai Lodge road represented the single carriageways. Waiyaki Way and Southern Bypass plies through both Nairobi and Kiambu Counties; Magadi road links Nairobi County with Kajiado County while Nairobi – Nakuru Highway plies through Nairobi, Kiambu, Nyandarua and Nakuru counties.

Waiyaki Way and Magadi road represented urban settings while the Nairobi – Nakuru Highway represented both the rural and urban settings with a mix of single carriageways and dual carriageways. The roads composed of all the required study features including different road patterns and terrains.

3.3 LOGICAL AND ETHICAL CONSIDERATIONS

The study was authorised by the National Commission for Science Technology and Innovation (NACOSTI) of Kenya as evident in Appendix J. The permit allowed for the study to be carried out any part of Kenya.

3.4 THEORETICAL FRAMEWORK

A human vehicle driver operates in a complex multiagent environment. Hence, the modelling of a vehicle driver requires a proper characterization of his/her environment. The complexity of such a model stems from the fact that drivers operate under: partially observable; dynamic; nondeterministic; continuous; sequential; multiagent; and unknown environments. According to Russell and Norvig [59], such an environment is the hardest case for modelling since it entails analysing huge amounts of rich multimodal data gathered under diverse conditions. To achieve these, a combination of data gathering sensors and analysis techniques and methodologies is required. The research hence developed an agent that runs in parallel with a human vehicle driver as outlined in Figure **3.1**. An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors [59].

The human driver uses its own perceptions while the driver agent uses GPS data and proximity sensor data as its percepts as shown in Figure 3.1. Perceptions for both agents are affected by the surrounding environment and vehicle status. They however undertake similar actions, namely, speeding, accelerate, decelerate, stop and turn. As a result, the performance measures relate to behavioural analysis and operational environment detection. The study limited the behavioural analysis to speeding behaviour, acceleration behaviour, deceleration behaviour, stopping behaviour and cornering behaviour. Detection of the operational environment was limited to road terrain and road pattern.

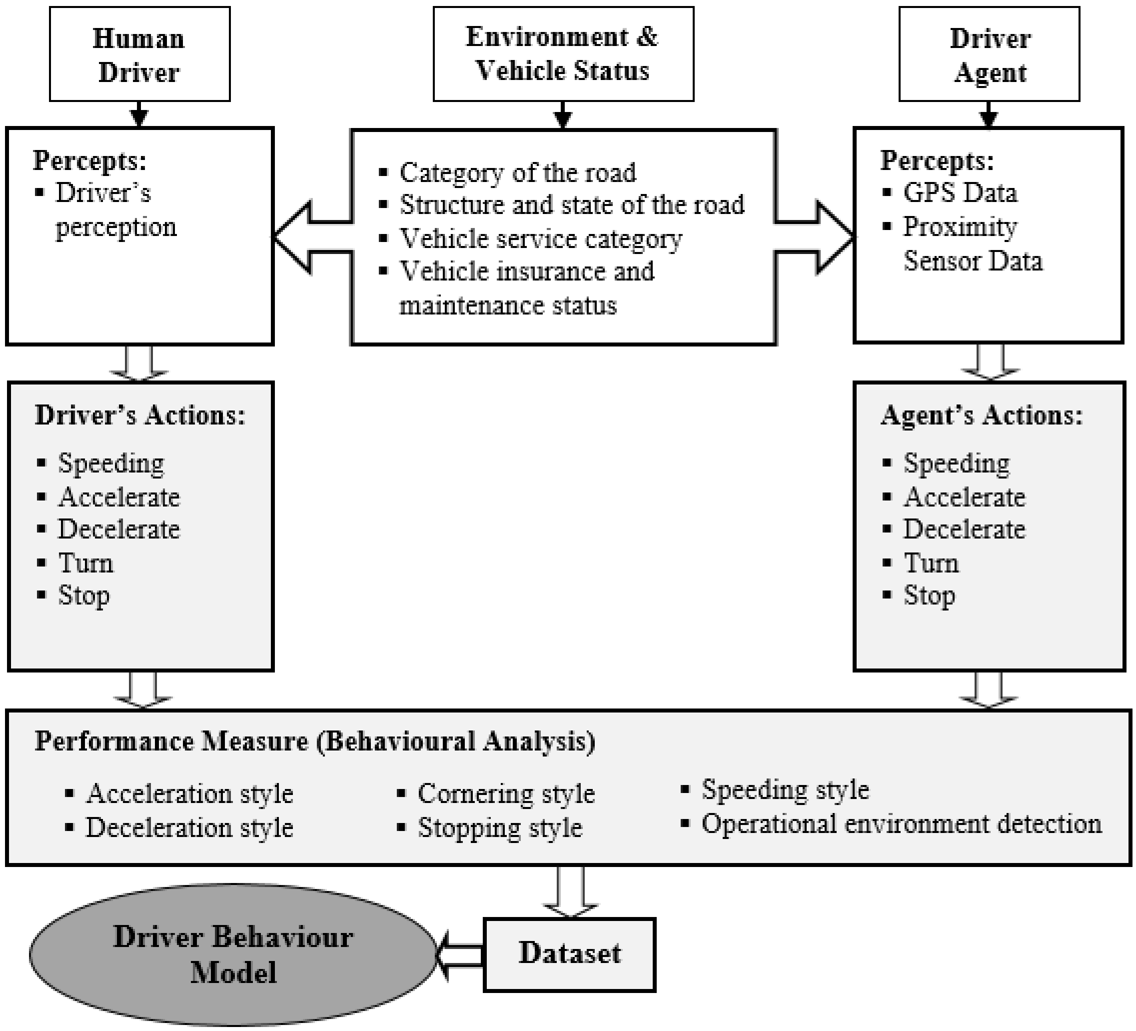


Figure 3.1. The Driver Agent's Theoretical Framework

The driver agent in this study does not activate mechanical effectors, it instead operates as a software agent. Hence, the performance measures were speeding, acceleration, deceleration, cornering and stopping styles. Furthermore, detection of the operational environment was also a performance measure for the agent. These performance was evaluated using the confusion matrix. The performance was hence gauged based on accuracy, precision, recall and F-score as provided by the confusion matrix, where,

i) Accuracy is a numeric measure of how good an agent algorithm is.
ii) Precision represents the fraction of agent actions that are relevant.
iii) Recall represents the fraction of agent actions that were undertaken.
iv) F-score is a tradeoff of precision against recall.

A task environment includes the performance measure, the external environment and the sensors. Figure 3.1 outlines a comparison between a human driver and the proposed driver agent in a different perspective as a way of expounding on the theoretical framework. The analysis is based on five main factors, namely, environment, sensors, effectors, actions with performance measured based on confusion matrix percentage outcomes.

Table 3.1. Comparison between the Human Driver and the Driver Agent

Agent Type	**Environment**	**Sensors**	**Effectors**	**Actions**	**Performance Measures**
Human Driver	▪ Type and state of Road ▪ Other road users ▪ Type and state of vehicle ▪ Obstacles	▪ Eyes	▪ Hands ▪ Feet	▪ Speed ▪ Accelerate ▪ Decelerate ▪ Stop ▪ Turn	Actual behaviour with respect to: ▪ Speeding ▪ Acceleration ▪ Deceleration ▪ Stopping ▪ Cornering Operational Environment detection
Driver Agent	▪ Type and state of Road ▪ Other road users ▪ Type and state of vehicle ▪ Obstacles	▪ GPS receiver ▪ Proximity sensor	Functions for actions to be taken on effectors: ▪ Speed() ▪ Accelerate() ▪ Decelerate() ▪ Stop() ▪ Turn()	Dashboard display of actions: ▪ Speed ▪ Accelerate ▪ Decelerate ▪ Stop ▪ Turn	Accuracy, precision and recall evaluations for: ▪ Speeding ▪ Acceleration ▪ Deceleration ▪ Stopping ▪ Cornering Operational Environment detection

According to Table 3.1, both agents operate in a similar type of environment affected by state and type of roads, state and type of vehicles and other road users. The human agent in this study is limited to eyes as the main sensor while the driver agent uses a GPS receiver and a proximity sensor as its main sensors. The study limited both agent actions to speed, accelerate, decelerate, stop and turn based on the study scope. The fact that the driver agent is a software agent, dashboard display of the various actions was used. To actualise the various actions, the human driver uses hands and feet while the driver agent calls and executes the various software functions for the actions, namely, speed(), accelerate(), decelerate(), stop() and turn(). Both agents' performance measures were limited to five behavioural analyses, that is, speeding behaviour, acceleration behaviour, deceleration behaviour, stopping behaviour and cornering behaviour. Another performance measure was the detection of the operational environment, limited to road terrain and road pattern.

3.5 CONCEPTUAL FRAMEWORK

Figure 3.2 shows the conceptual framework, outlining independent, dependent and intervening variables. The independent variables are GPS data collected by GPS receivers. These are coordinates, speed, altitude, time, direction, and GPS signal strength. In addition, obstacle data collected by the proximity sensor was also as an independent variable. These variables were determined and selected through a prestudy mapping them to dependent variables. Since behaviour is not measurable, the study made useful conclusions about a number of factors that determine behaviour. The dependent variables hence included a measure of parameters that contribute to the driving style of a human vehicle driver. These are speeding trends, acceleration trends, deceleration trends, stopping trends and cornering trends. These trends founded the driver's profile that formulated a dataset that was used to train, evaluate and test the vehicle driver agent. Detection of the vehicle driver's operational environment, limited to road pattern and road terrain was also a dependent variable. Intervening variables considered in this study were road category that could be either dual carriageway, single carriageway or highway; structure and state of the road with respect to straightness, corners, bumps, sloppiness and condition of the road; vehicle service category that could be either public service or private service and vehicle insurance and maintenance status that determines road worthiness.

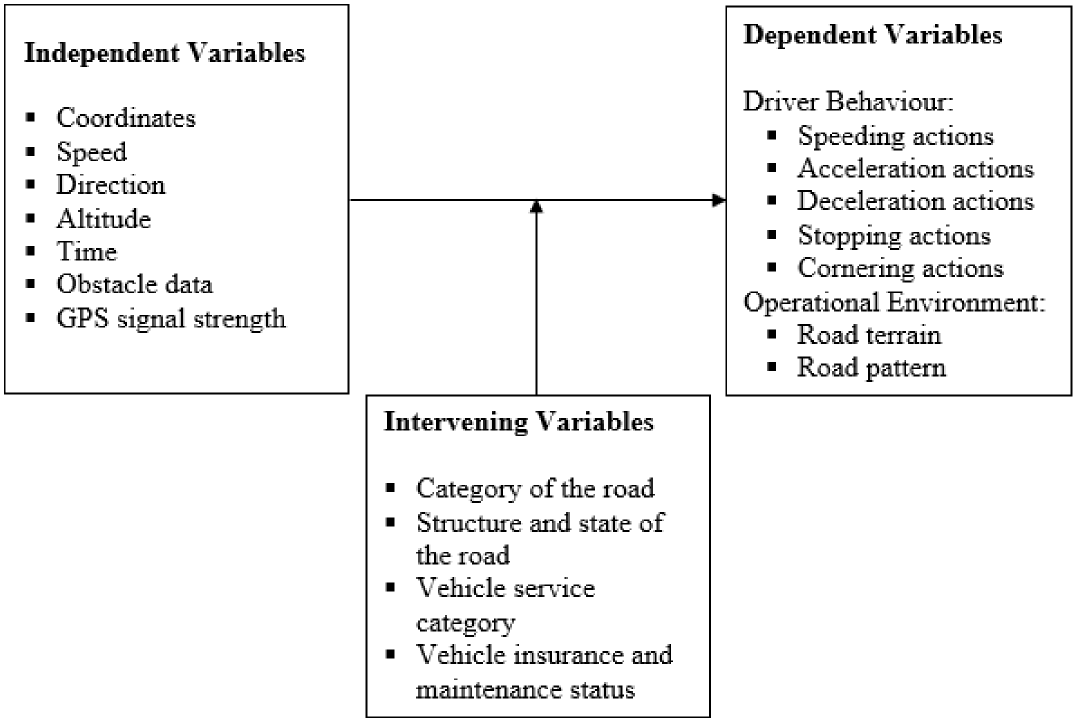


Figure 3.2 Conceptual Framework

It is worth noting that each independent variable may have a direct effect, limited effect or no effect at all over a given dependent variable. Table 3.2 outlines the effects of each independent variable over the dependent variables. Similarly, Table 3.3 outlines the effects of intervening variables over the dependent variables, where it clearly appears that all intervening variables have a direct effect on driver behaviour but no effect on the determination of the operational environment.

Table 3.2. Effects of Independent Variables over Dependent Variables

Independent Variable	**Effect of Dependent Variables**
Coordinates	▪ Changes in coordinates directly affect the determination of the operational environment. ▪ Changes in coordinates have a limited effect to speeding, acceleration, deceleration, cornering and stopping actions.
Speed	▪ Changes in speed directly affect speeding, acceleration, deceleration, cornering and stopping actions. ▪ Changes in speed have a limited effect on the determination of the operational environment.
Direction	▪ Changes in direction directly affect the determination of the road pattern. ▪ Changes in coordinates have a limited effect to speeding, acceleration, deceleration, cornering and stopping actions and no effect towards the determination of the road terrain.
Altitude	▪ Changes is altitude directly affect the determination of the road terrain. ▪ Changes in altitude have a limited effect to speeding, acceleration, deceleration, cornering and stopping actions and no effect towards the determination of road pattern.
Time	▪ Changes in time directly affect determination of driver behaviour and operational environment.
Obstacle data	▪ Obstacle data directly affect speeding, acceleration, deceleration, cornering and stopping actions. ▪ Obstacle data has no effect on the determination of the operational environment.
GPS signal strength	▪ GPS signal strength at any given point in time directly affect determination of driver behaviour and operational environment.

Table 3.3. Effects of Intervening Variables over Dependent Variables

Intervening Variable	**Effect of Dependent Variables**
Category and structure of the road	▪ The category of the road directly affects speeding, acceleration, deceleration, cornering and stopping actions. ▪ The category of the road has no effect in the determination of the operational environment with respect to road terrain and pattern.
Structure and state of the road	▪ The structure of the road directly affects speeding, acceleration, deceleration, cornering and stopping actions. ▪ The structure of road has no effect in the determination of the operational environment with respect to road terrain and pattern.
Vehicle service category	▪ The vehicle service category directly affects speeding, acceleration, deceleration, cornering and stopping actions. ▪ The vehicle service category has no effect in the determination of the operational environment with respect to road terrain and pattern.
Vehicle insurance and maintenance state	▪ The vehicle insurance and maintenance state directly affect speeding, acceleration, deceleration, cornering and stopping actions. ▪ The vehicle insurance and maintenance state has no effect in the determination of the operational environment with respect to road terrain and pattern.

3.6 SYSTEM MODEL

3.6.1 THE BLOCK DIAGRAM

The block diagram in Figure 3.3 outlines five major components that formulates the system model, namely, GPS satellite, GPS receiver, Data Collection Unit (DCU), Server and Terminal.

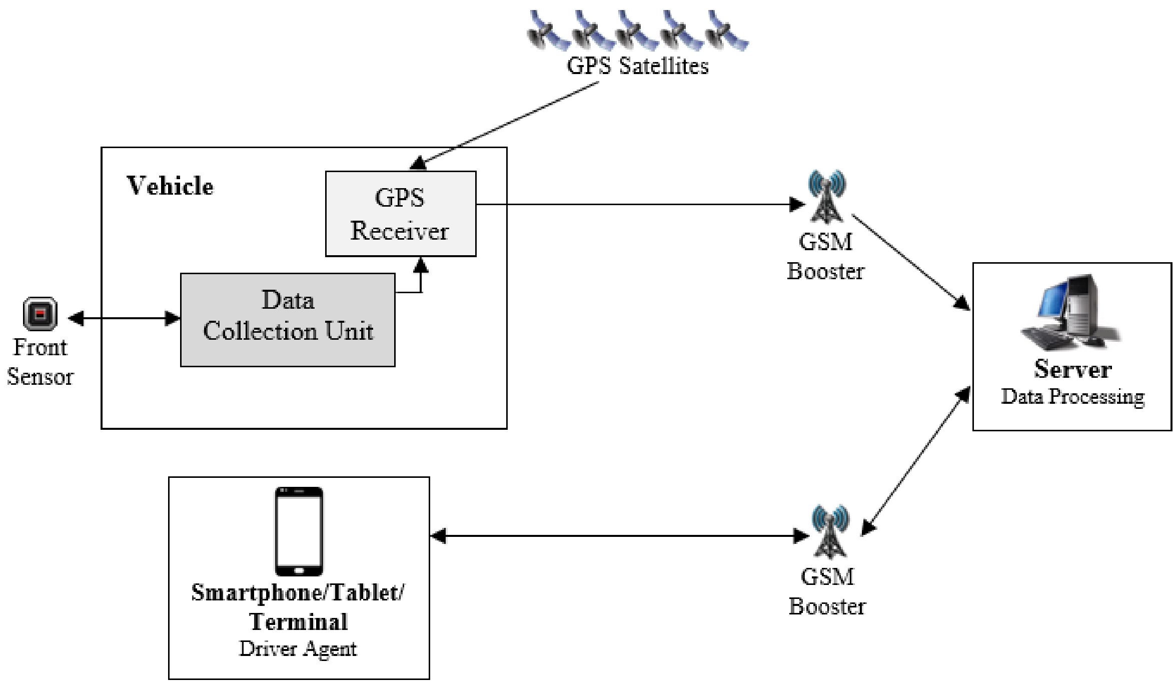


Figure 3.3. The System Model

According to the model, GPS satellites continuously transmit signals containing satellites' positions (orbit), the time the signal is sent and other data. GPS receivers installed in sample vehicles process the satellite signals to achieve position, time and other data parameters. A Data Collection Unit connected to ultrasonic proximity sensors on the test vehicle determined obstacle presence or absence. The DCU conveys sensor signals to the GPS receiver to complement GPS data. Upon receipt of DCU data, the GPS receiver packages all the data in a single message then transmits to a server via GPRS. The data is transmitted at varied intervals less than 5 seconds. The server performs data analysis using specialised probabilistic methodologies to establish patterns of vehicle driver behaviour. The software driver agent running on the terminal periodically gets and displays analysed data as an indicator of human vehicle driver behavioural probabilities and agent proposed actions.

3.6.2 GPS TECHNOLOGY

The model adapts the GPS technology where Automatic Vehicle Location (AVL) is a technology to track vehicles and relay location information to centralised monitoring locations [60]. A variety of technologies can be used in this regard for instance satellite option that incorporates GPS. GPS refers to a United States of America's Government-operated network of earth-orbiting satellites with ground control stations [61]. The network with approximately 24 active satellites participating at any point in time continuously provides time and position information to receiving stations and devices around the globe [61], [62].

A Global Position System is made up of three parts: GPS satellite, GPS receiver and a monitoring station. A GPS satellite transmits a signal containing the satellite's position (orbit), the time the signal was sent and other data at a frequency of 1575.42MHz. A GPS receiver uses the difference between the time the signal was sent and when it was received to calculate its distance from the satellite. GPS positions [61], [63] are calculated through triangulation where the known positions of at least three satellites overhead determine the position of a GPS receiver/antenna pair on Earth. A signal from a fourth satellite is used for time corrections since the clock in a GPS receiver is not as accurate as the atomic clock used by GPS satellites.

An algorithm that employs the doppler shift in the pseudo range signals from the satellites is used to compute vehicle speeds. The doppler shift is directly proportional to the velocity of the receiver along the direction to the satellite, regardless of the distance to the satellite [64]. For better accuracy, speeds are updated at short intervals with readings normalized. Other parameters supplied by the satellite include: date; time; and altitude. Upon acquisition of these data, a GPS receiver sends the logged data updates to a monitoring station via GPRS for analysis. This event occurs at some pre-set time intervals or upon a trigger.

3.6.3 THE LEARNING AGENT

A utility-based agent uses a model of the world, along with a utility function that measures its preferences among states of the world [59]. It chooses actions that leads to the best-expected utility, where expected utility is computed as an average of all possible outcome states, weighted by the probability of the outcome. A rational utility-based agent chooses an action that maximizes the expected utility of the action outcomes. Ingenious algorithms are required for utility maximization. Despite these algorithms, perfect rationality is usually unachievable in practice due to computational complexities [59]. The nature of the agent's environment is partially observable, multiagent, stochastic, sequential, dynamic, continuous, and unknown. Mathematically, an agent's behaviour is described by the agent function that maps any given percept sequence to an action [59].

The research problem is a contingency kind of problem since exact prediction is impossible and its solution requires a strategy, a contingency plan that specifies what action to take based on the received percepts. Thus the use of utility functions to provide agent's internal performance measures in two main perspectives. Firstly, the function offers appropriate tradeoffs amongst conflicting goals. Secondly, it weighs success likelihood against the importance of goals. If the internal utility function and the external performance measures are in agreement [59], then it chooses actions to maximize utility.

The intelligence of the agent is based on its dataset where the learning mechanism is a combination of supervised and reinforcement learning subsystems. At the initial stages, it is adapted to the dataset through supervised learning. The supervised learning is achieved through the machine learning process, namely, training, validation and testing. Reinforcement learning is gradually mainstreamed in the supervised learning at the point of validation and testing. Reinforcement learning where the agent learns from a series of rewards or punishments that attribute to reinforcement [59]. A reward is a form of feedback that makes the agent know whether something good or bad has happened based on its actions. The reward-based approach lead to formulation of an optimal behavioural pattern dataset. Learning allows the agent to initially operate in unknown environments and to become more competent than its initial knowledge. Figure 3.4 outlines the structure of a learning utility-based agent.

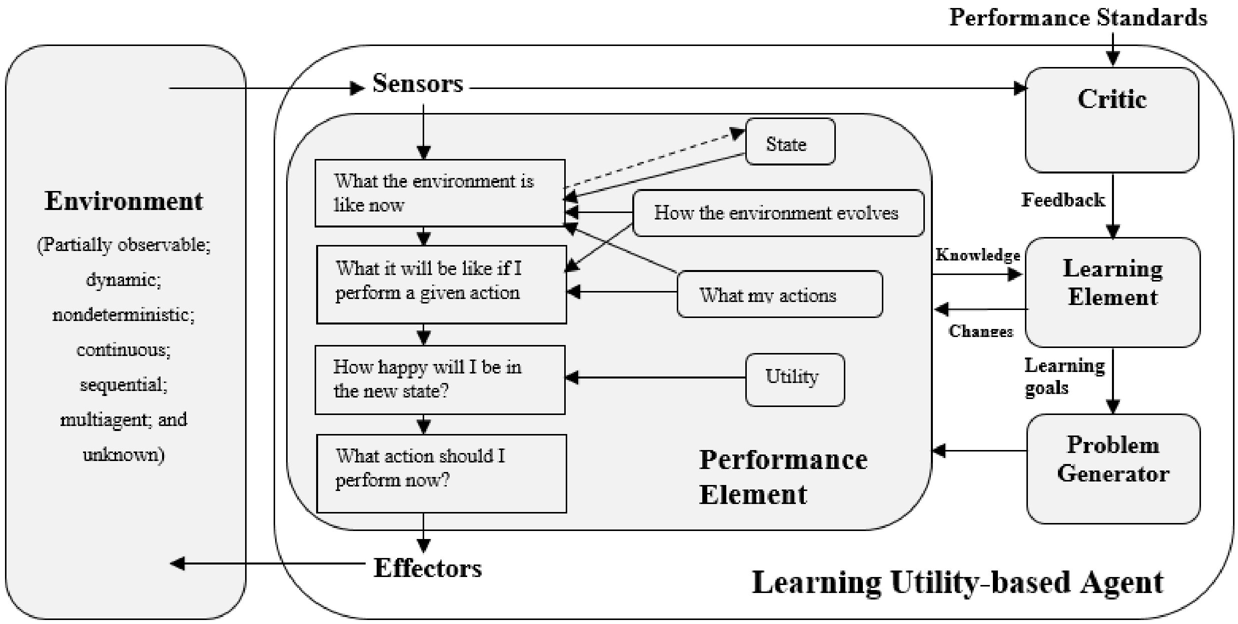


Figure 3.4. The Structure of the Learning Utility-based Driver Agent

In an ideal case, learning agents act autonomously, operate in unknown environments, synthesise rules and/or patterns from volumes of data, handle complex data as they improve their own performance. This means that percepts are not only used for acting but for improvement on future performance. A learning utility-based agent hence comprises of four key elements, namely, a learning element, a critic, a performance element and a problem generator as illustrated in Figure 3.4, where,

i) The performance element is responsible for selecting external actions. This actions are based on percepts detected by the sensors. The performance element also takes in change percepts from the learning element to decide on actions to be undertaken. Feedback from the problem generator also acts as input to the performance element, facilitating continuous learning. On the other hand, the performance element has two output channels: knowledge to the learning element and action signals to effectors.

ii) The critic is responsible for providing feedback to the learning element. The feedback is an outcome of processed input from sensors in comparison with objective performance standards outside the agent. For a utility-based agent, as for the case of this study, an external performance standard is critical to tell the critic if the agent's action has a good or bad effect on its environment.

iii) The learning element is responsible for making improvements to the agent's performance. Learning is achieved through observing pairs of successive states in the percept sequence. From this, the agent can learn how the world evolves. The element uses feedback from the critic on how well the agent is doing. This feedback is used to determine how the performance element should be modified as an improvement of the agent for better performance in future. Furthermore, knowledge from the performance element is also fed to the learning element for analysis aimed at future performance improvements. There are two outcomes from the learning element that act as input to the other elements. These are the change output that acts as input percept for the performance element and the learning goals output that acts as input percepts to the problem generator.

iv) The problem generator suggests actions that lead to new and informative experiences. This actions suggestions are continuously fed to the performance element as of when they are determined. This makes the agent to keep learning and improving on performance. The problem generator relies on learning goals generated by the learning element to make its decisions.

3.7 DATA COLLECTION PROCESS

3.7.1 SOURCES OF DATA

Data was collected from drivers driving sample vehicles at different road segments. These vehicles were instrumented with various sensors for data collection. The study used a GPS receiver type capable of providing vehicle position coordinates, speed, direction (angle), altitude and timestamp. A proximity sensor generated obstacle data with data transferred to the GPS receiver for subsequent transmission to the server. On the other hand, operational rules per type of road and driving region was based on regulations set out by the National Transport and Safety Authority (NTSA) in Kenya and other World standard metrics.

3.7.2 TARGET POPULATION

Kenya has approximately 3,000,000 registered vehicles each of which could be assumed to be operated by one or more licensed driver. Hence, the number of vehicle drivers is estimated to be slightly above the number of registered vehicles. A target population refers to the collection of individuals or regions to be used in a given investigation or study [65]. The target population for this study were licensed vehicle drivers in Kenya. The study was based on a target sample comprising 30 drivers subjected to two instrumented private cars and fifteen instrumented Public Service Vehicles.

3.7.3 SAMPLING AND SAMPLE SIZE

A sample is a finite part of a statistical population to be investigated [65]. When dealing with people, it can be defined as a set of respondents selected from a larger population for the purpose of a survey. The choice of a sample influences the degree of accuracy of the results in a research about a given phenomenon. Scholars have argued that where time and resources allow, the entire population can be studied [65], [66]. While this may seem as the best possible approach, it is practically impossible. The Cochran [67] provides one of the ideal methods for deriving a sample size when given a desired level of precision, desired confidence level and the estimated proportion of the attribute present in the population. The formula is considered appropriate in situations with large population sizes. Equation (1) shows the Cochran formula.

$$n_0 = \frac{Z^2 pq}{e^2} \qquad (1)$$

Where:

i) e is the desired level of precision, commonly referred to as the margin of error.
ii) p is the (estimated) proportion of the population having the attributes in question
iii) q is 1 – p.
iv) The z-value is found in the Z table.

Considering a confidence level of 95%, a Z value of 1.96 would be applicable as per the standard Z table and a margin of error of 5%. The p was put at 0.5 which translates to a q of 0.5. Hence, the n_0 was determined to be 385 as outlined in equation (2).

$$n_0 = \frac{1.96^2(0.5)(1-0.5)}{0.05^2} \qquad (2)$$

To try and fit the sample size determination to an approximate population of 3,000,000 licenced drivers in Kenya, equation (3) was used to modify the sample size.

$$n = \frac{n_0}{1+\frac{(n_0-1)}{N}} \qquad (3)$$

Where:

i) n_0 is the Cochran's sample size recommendation.
ii) N is the population size, in this case 3,000,000.
iii) n is the new adjusted sample size.

Hence, the resulting sample size after the modification was 384.95 which still rounds off to 385. The computation is as outlined in equation (4). The small deviation of 0.05 is an indicator that the initial Cochran formula fits in large populations, hence, the modification will have a significance only on smaller populations.

$$n = \frac{385}{1+\frac{(385-1)}{3,000,000}} \qquad (4)$$

Hair et al [68] argues that the sample size can range from 30 to 500 respondents but further states that the use for analysis may also dictate the sample. In a later publication, Hair et al [69] notes that if the sample size is less than 30, significant departures from normality can have a substantial impact on the results. The minimum is to have at least five times as many observations as the number of variables to be analysed [69], particularly in cases where factor analysis is involved.

MacCullum et al [70] stated that where there is need to generalize the findings, as may be the case in this study, sample size cannot be the sole determinant of generalizability of the results; adequacy of a sample in such cases should be evaluated by examining the level of bias and the level of data quality, which are two critical components. According to [71], studies of new ideas often start small, sometimes even with an n of 1, due to cost and feasibility concerns. The cost of the study is always impossible for researchers and funders to overlook in sample size determination [71], [72].

This study hence used a sample size of 30 drivers with a thorough consideration of other critical factors that guaranteed validity of the sample, including: high level of data quality, minimal bias and high level representativeness. The number of drivers to be involved was constrained by the cost of the GPS receivers, proximity sensors and other accessories. It is however worth noting that for a single driver, the system generates tones of data for analysis. This hence, takes care of the lean number of drivers involved in the study, as such, the results are not affected either.

Several sampling techniques exist whose choice depends on the type of study being carried out. In this study, stratified simple random sampling technique was used in the selection of the 30 drivers, vehicles to be involved and test road segments as follows:

i) Two strata categorised drivers and vehicles, namely, public service and private service.
ii) Three strata categorised road segments, namely, short distance dual carriageways, short distance single carriageways and long distance highways.

Table 3.4. Sampling Grid

Category of Vehicle	**Category of Road**	**Number of Drivers**
Public Service	Short distance dual carriageway	5
	Short distance single carriageway	5
	Long distance highway	5
Private Service	Short distance dual carriageway	5
	Short distance single carriageway	5
	Long distance highway	5
Total: 2	**Total: 6**	**Total: 30**

The sampling grid in Table 3.4 shows the number of drivers sampled from each vehicle category and road category. These choices based on a number of assumptions as outlined in section 1.6. It was hence assumed to be a full representative of the driving styles, types of vehicles and operational environments. A target sample of two Private Service Vehicles and fifteen Public Service Vehicles was used. A set of 15 drivers from the Private Service Vehicle category and 15 drivers from the Public Service Vehicle category were subjected to the sampled instrumented vehicles on specific routes for behavioural pattern analyses. The two broad Service Vehicle categories accommodate light, heavy and commercial vehicle subcategories. A driver behavioural pattern dataset was formulated purely from gathered and analysed GPS data. The dataset from select drivers whose behaviour met the required conditions was used to train, validate and test an agent modelling human vehicle driver behaviour. The full driver behaviour model acts as a software driver agent with screen display of actions running in parallel with a human vehicle driver without activating any mechanical effectors.

3.7.4 DATA COLLECTION TOOLS AND TECHNIQUES

A research data collection tool is defined as a testing device that measures a given phenomenon. This study used real-time data collection using the following tools:

i) GPS Receiver

   Continously receives GPS data from GPS satelittes and transmits to the GPS server for analysis.

ii) Data Collection Unit (DCU)

   Collects obstacle data to complement GPS data. It transmits obstacle signal data to the GPS receiver for subsequent transmission to the GPS server.

iii) GPS Server

   Receives data from GPS receivers and stores in the database for analysis.

3.7.4.1 DESIGN AND DEVELOPMENT OF DATA COLLECTION TOOLS

The prototype comprises of a GPS receiver, a Data Collection Unit and a GPS server. The study used GPS receivers based on the GPRMC sentence format. These were sourced and used as per the manufacturer’s specifications. It should be noted that the National Marine Electronics Association (NMEA) 0183 standard defines dozens of sentence formats, but only a fraction applies directly to GPS receivers [73]. NMEA 0183 data transmissions use plain text with the characters coded using seven-bit American Standard Code for Information Interchange (ASCII) [73]. The Recommended Minimum Specific GPS/Transmit Data (RMC) sentence contains Coordinated Universal Time (UTC) date and time, the latitude and longitude of the position fix, the ground speed, the course over the ground with respect to the true north, and the magnetic declination [73]. The data is send as one sentence starting with $$ and ending with ## with the various data parameters separated by commas [74]. The following is an example of the sentence as transmitted by the GPS receiver:

$$1000000002???&A9955&B051006.000,A,0117.8458,S,03650.5808,E,30.00,090.38,200418,,,
A*79|0.9|&C0000011111&D0026:164&E10000000&Y00180000##

Where:

1000000002	Device unique identifier (Maximum of 15 characters)
A9955	Device board ID (Manufacturer specific)
051006.000	Time (hhmmss.ddd)
A	Validity of the fix (A = Valid)
0117.8458	Latitude (ddmm.mmmm)
S	Latitude hemisphere (S = Southern)
03650.5808	Longitude (dddmm.mmmm)
E	Longitude hemisphere (E = Eastern)
30.00	Speed in knots (s.s)
090.38	Course in degrees (h.h)
200418	Date (ddmmyy)
'$' ',' '?' '&' and '#'	Separator to the various data parameters

The string "A*79|0.9|&C0000011111&D0026:164&E1000 0000&Y00180000" represents proprietary data that the device tracked along the way. This data is usually secreted by the device manufacturers with *79 representing the checksum.

The format provided key data parameters required for driver behaviour monitoring. A custom-made Data Collection Unit (DCU) complemented GPS receiver's data with obstacle data. It was based on an Arduino Microcontroller with an ultrasonic proximity sensor as outlined in Figure 3.5 with the source code for the program controlling the Arduino microcontroller outlined in Appendix A.

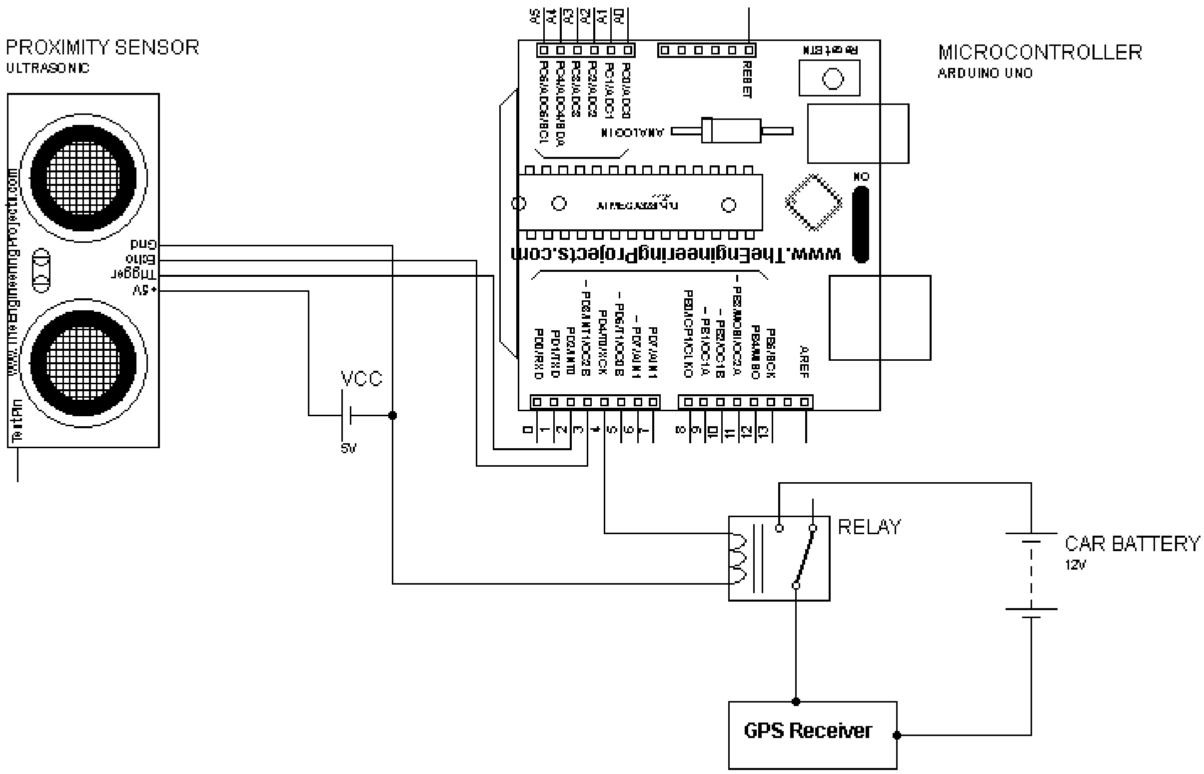


Figure 3.5. Circuit Diagram for the Data Collection Unit

The DCU periodically sends trigger signals to proximity sensors on test vehicle for determination of obstacles in range. It then conveys sensor signals to the GPS receiver via a power relay that completes the circuit if there is an obstacle otherwise it opens the circuit.

Microcontroller (Arduino Uno)

Arduino is an open-source computer hardware and software company, project and user community that designs and manufactures kits for building digital devices and interactive objects that can sense and control the physical world [75]. An Arduino board consists of an Atmel 8-bit Alf and Vegard's RISC (AVR) microcontroller with complementary components that facilitate programming and interfacing with other circuits through a specially designed printed circuit board (PCB) [75], [76]. The Arduino integrated development environment (IDE) is a Java-based cross-platform application that includes a code editor that has features like other code editors. The IDE facilitates writing, compiling and uploading of programs to the Arduino board. An executable cyclic Arduino program requires a definition of only two functions, namely, setup and loop functions as shown in the microcontroller program in Appendix A.

An Arduino board takes direct current (DC) from a DC power source or an AC-to-DC adapter. It can also draw power through a Universal Serial Bus (USB) connection to any USB supported device. The microcontroller is programmed using a C or C++ based Arduino programming language. The wiring software library in the Arduino IDE makes many common input/output operations much easier [75]. The main features of an Arduino Uno board are: ATmega328P microcontroller, 7 – 12 input voltage, 14 digital input/output pins, 6 analog inputs, 32k flash memory, 16Mhz quartz crystal clock speed, USB connection, Power jack, In-Circuit Serial Programming (ICSP) header and the Reset button. Six out of the 14 digital input/output pins are Pulse Width Modulation (PWM) outputs, allowing analog results to be retrieved through them.

Proximity Sensor (HC-SR04)

The HC-SR04 proximity sensor is an obstacle detection sensor type based on ultrasound technology. It is a low cost sensor that provides 2cm to 400cm of non-contact measurement functionality. The sensor supports a ranging accuracy that can reach up to 3mm. The HC-SR04 module is composed of an ultrasound transmitter, a receiver and a control circuit. It has 4 pins: a 5 volts' pin for power, a trigger pin for trigger signal, an echo pin to receive the reflected signal and a ground pin. Table 3.5 outlines the technical specifications for the HC-SR04 ultrasonic sensor used in this study. This is as specified in the manufacturer's product datasheet.

Table 3.5. HC-SR04 Technical Specifications

Description	**Rating**
Working Voltage	DC 5V
Working Current	15mA
Working Frequency	40Hz
Max Range	400cm
Min Range	2cm
Measuring Angle	15 degree
Trigger Input Signal	10 μS TTL pulse
Echo Output Signal	Input TTL lever signal and the range in proportion
Dimension	45*20*15mm

Power Relay (5V DC SPDT)

The 5 Volts Direct Current (DC) Single Pole Double Throw (SPDT) is a power relay module that can be controlled directly by a wide range of microcontrollers. These microcontrollers include, Arduino, Alf and Vegard's RISC (AVR), Peripheral Interface Controller (PIC), Advanced RISC Machines (ARM) and Mixed Signal Processor (MSP) 430. The relay is suitable for numerous applications in the range of domestic appliances, office machines, audio equipment, automobiles among other appliances.

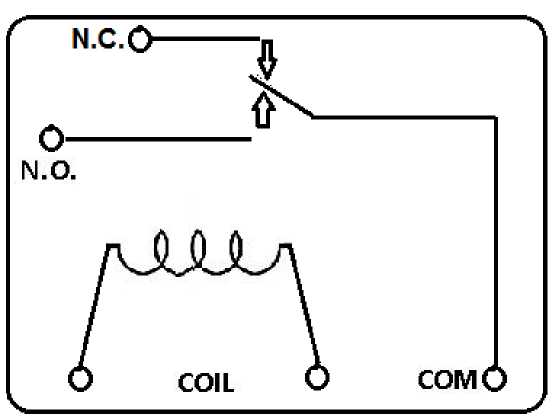


Figure 3.6. Internal Layout for a Power Relay

The 5V DC SPDT power relay has 5 pins as shown in Figure 3.6. These are the COM pin, Normally Connected (NC) to COM pin, Normally Open (NO) to COM pin, two 5 volts' COIL pins. The NC and NO pins enable it to act as a power switch for driving high voltage devices. The two COIL pins are supplied with 5 volts in either direction, creating a magnetic effect on the COIL that facilitates switching between NO and NC pins through attraction and release as shown in Figure 3.6. The COM to NO or NC connects to appliances or circuitries that supports high voltages. In this case, they connect 12 volts' power from the car battery to the GPS receiver. This is used to denote presence or absence of an obstacle.

Microcontroller Program

The flowchart in Figure 3.7 outlines the flow of events as the microcontroller sends trigger messages to the proximity sensor during the process of obstacle detection. An obstacle is detected if it falls within a 4-meter range, that was the operational sensing distance for the proximity sensor used in the study. Upon detection of an obstacle, the GPS trigger PIN is set to HIGH. As a result, the GPS data sent to the server will include a value that indicates detection of an obstacle. Otherwise the GPS trigger PIN is set LOW as an indicator that no obstacle is detected. The process occurs as a continuous loop as long as the vehicle engine is on.

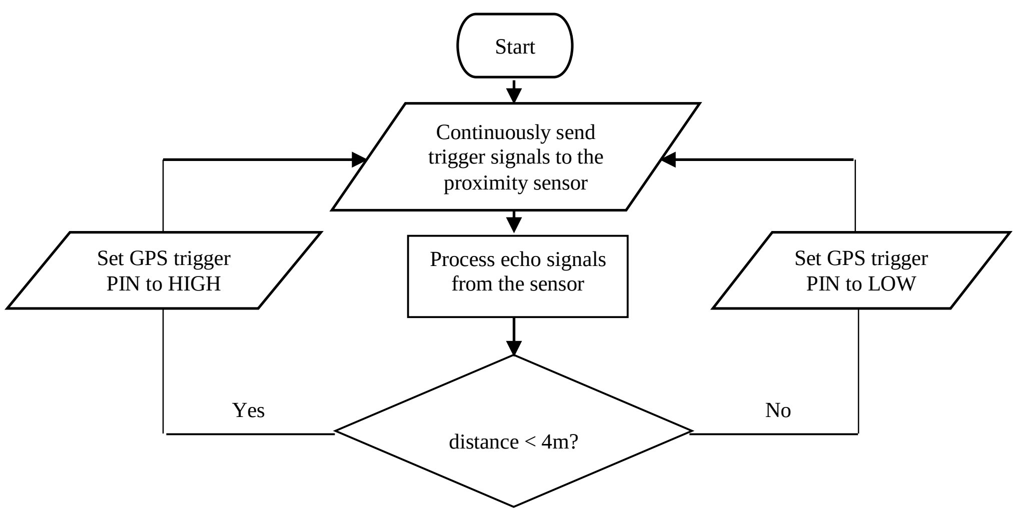


Figure 3.7. Microcontroller Communication with the Proximity Sensor

The Arduino Uno microcontroller was programmed with the source code outlined in Appendix A. Line 20 of the source code provides room for adjustment of obstacle sensing distances as a way for calibration of the model. If an obstacle is detected within the specified distance range in centimetres, then line 21 is executed. This would set the GPS trigger pin, in this case referred to as the gpstrigpin, to HIGH. On the other hand, if no obstacle is detected within the range, line 24 will be executed setting the gpstrigpin to LOW.

GPS Receiver

The study used on-board units that use GPS technology to collect data from GPS satellites then transmit the data to a GPS server for processing using GPRS technology. The choice of the devices was informed by the required parameters that include vehicle speed, altitude, direction and a timestamp.

GPS Server

The data transmitted by a GPS receiver ends up on a GPS server that has a receiver application running continuously with a specific open port listening to incoming connections. A GPS server was developed with two main components: -

i) **Data Receiver TCP Application** – the application interface receives data from GPS receivers in National Marine Electronics Association (NMEA) format, interpret, transform then route the data to the database for storage. The application uses socket communication.

ii) **SQL Based Database** – the SQL-based database stores the data awaiting analysis.

A Data Receiver TCP application creates a specific type of socket used to listen to client requests, in this case, GPS receiver connection requests. In case of a connection request, the application creates a new socket through which exchange of data with the client using input and output streams will be facilitated. The source and destination IP address, and port number constitute a network socket. The process can be summarized as follows:-

i) The server process binds an IP address to a port then continuously listens to client requests. The port must be opened on the router within the network that the server is setup.

ii) The client, in this case, GPS receiver configured with the server IP address and port number contacts the server by creating a client-local TCP socket, specifying IP address and port number of the server. As a result of this, the client TCP establishes a connection to the server TCP.

iii) When contacted, the server TCP creates a new socket for the server process to communicate with the client there by allowing the GPS receiver to transmit data to the server over the IP layer using either UDP or TCP. The GPS receivers used in this study transmitted data using TCP. The transmission was via GPRS based on the mobile service provider's SIM used.

iv) The data receiver application receives the packets, validates them against authenticated devices using a specific unique unit identifier and then stores in a database. The unique identifier is always predefined in the database during initial unit setup.

The flow chart in Figure 3.8 outlines the functions of the GPS Data Receiver from the time GPS data is received from the GPS receiver to the time it is routed to the GPS SQL-based database. An SQL-based database was used since the data was relational. Ten tables were created to store the various data elements. Appendix C outlines the ten tables with their respective attributes and data types that formulates the database schema.

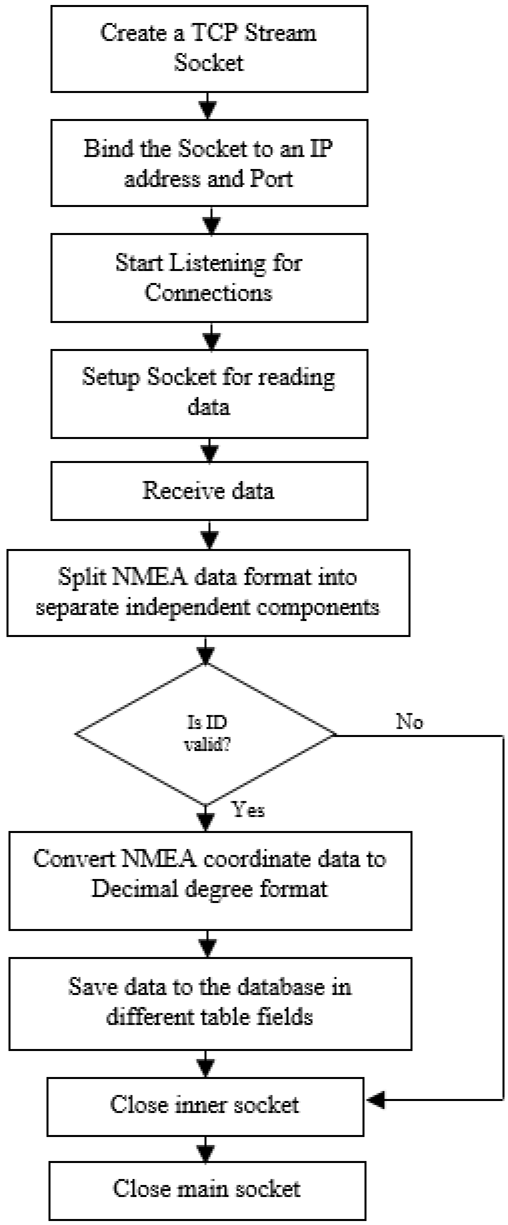


Figure 3.8. Flowchart of Events at the Data Receiver

3.7.4.2 VALIDITY AND RELIABILITY OF DATA COLLECTION INSTRUMENTS

Measurement errors could arise from faults in the instruments, incorrect interpretations of obtained values or instability in the behaviour of respondents or samples. These errors could be systematic or random. Systematic errors or bias occur when the errors are made in one direction away from the true score. Random errors on the other hand are attributable to chance factors.

According to Mugenda [77], validity is the degree to which a research instrument measures what it purports to measure. On the other hand, reliability is the extent to which results or observations for a given experiment are consistent on any repeated trials [77]. Reliability in other words, is the stability or consistency of scores over time or across raters.

In this study, the measurement instruments were on tested on five drivers in a pretest to check for any inconsistencies and/or errors. After the pretest, relevant adjustments were made to the instruments before use in the main study on the sampled subjects.

Data collection tools were validated through the following steps:

i) The first step involved face validity through dialog and brain storming with experts in the transport industry and through research seminars. This led to the formulation of the driver behaviour and environment probabilities per driving state chart as outlined in Table 0.1.

ii) A pilot study was then contacted involving 5 drivers on different road segments and vehicle models that generated an intense prestudy dataset. Appendix D outlines sample cleaned prestudy data. The dataset was cleaned and analysed using Principal Component Analysis and Factor Analysis to ascertain whether the key variables were coming out clearly. For instance, single factor, correlation and covariance ANOVA analyses were established on a varied set of key data parameters that include, speed, altitude, direction and change in time to determine the level of consistency and reliability before the actual study. Sample analysis results are as presented in section 4.1.1.4 on validation of data collection tools.

iii) Some revisions were made on the data collection tools. For instance, some thresholds were adjusted in the driver behaviour and environment probabilities per driving state chart as outlined in Table 0.1. Furthermore, GPS receivers were reconfigured to send data at slightly short time intervals to help capture all driving style instances.

3.8 DATA ANALYSIS AND PRESENTATION

3.8.1 DATA MANAGEMENT

An important aspect of this research was in maintaining high quality standards in data collection to ensure quality results. This was achieved through proper validation of data collection tools and proper storage of the collected data. The realtime data logged at the server was kept as raw as possible to facilitate proper analysis on the same. Most importantly, backups of the data were created and protected to maintain high data integrity.

3.8.2 DATA SCREENING

Based on the nature of data collection that was purely realtime and using technology in data collection, a check on missing values, normality and outliers in the data was done throughout the entire study. This ensured that the fundamental characteristics of the data were available and being collected appropriately.

3.8.2.1 MISSING VALUES

Given that data collection was electronic and automatically transmitted to the server by GPS receivers, some instances could have delays that could lead to missing values, leading to inconsistencies. A strategy was implemented to deal with such situations. This strategy involved analysis of data using algorithms that subjected the data to time series analysis such that huge gaps in time differences could lead to some data being eliminated from the analysis. The 2TBN algorithm was heavily relied upon in this regard.

3.8.2.2 OUTLIERS

Data representing the independent variables was thoroughly scruitnised to ascertain whether it was vital to influence the dependent variables. Instances in the data collection algorithms that could lead to extreme data points as a form of outliers were spotted with the algorithms adjusted accordingly to cleanse the data. It should be noted that the realtime nature of data collection employed in this study was prone such instances, where, the data for a given independent variable could have a huge deviation from other samples. During the entire study, outliers were determined and eliminated through multivariate normality analysis. To further avoid outliers in the main study, the 2TBN and Gaussian Mixture Model data analysis algorithms were adjusted to detect huge variances in data values and automatically eliminate the data from the analysis.

3.8.2.3 ESTABLISHING VARIABLE NORMALITY

Hypothesis testing technique was used to assess the relationship among various variables concurrently. Multivariate normality can be assumed [69], though the normality of the single variables is not guaranteed. The research determined skewness and kurtosis as the methods of normality. Skewness was used to measure the degree to which the distribution was symmetric, whereby; a negative value showed that the left side of the histogram was lengthier associated to the precise side. This is an optimistic worth demonstrating the opposite while a value zero indicates that the distribution is balanced. Kurtosis on the other hand, unhurried the competent highest of the unfriendly in the movement. Information distribution in high worth has the highest height nearby the unfriendly and finished. Low kurtosis has a horizontal top neighboring the unkind. Negative kurtosis showed platykurtic (flatter) distribution while positive values leptokurtic (peaked) distribution. All resulting statistical tests are invalid from the normal distribution if the variation is significantly larger [69]. This was applied throughout the study by analyzing skewness and kurtosis levels provided through descriptive statistics results as depicted in Chapter 5. At this point, some data was completely eliminated from the analysis for not meeting the requirements.

3.8.2.4 FURTHER DATA VALIDITY

According to Mugenda [77], validity of data depends on the degree to which extraneous variables have been controlled in the study to ensure that the change observed in the dependent variable is actually as a result of the treatment. Hence, in addition to checks on missing values and outliers, the following types of validity were considered:

1. Face Validity

   Experts, research supervisors and other scholars were engaged in seminars and workshops to ascertain whether the findings were valid.

2. Formative Validity

   A discussion of research findings complemented by face and construct validity was used to assesses how well the measures were able to provide information to help in driver behaviour modelling.

3. Experimental Validity

   Experimental validity was looked at in two perspectives, namely, internal validity and external validity. Internal validity explored whether the independent variables influenced the dependent variables. This was tested during the prestudy at the point of determining the required data parameters that informed the selection of independent variables. The fact that the prestudy yielded promising results, it was a clear indicator that the independent variables were clearly affecting the dependent variables. Prestudy results are as outlined in Chapter 4, section 4.1. On the other hand, external validity was used to ascertain whether study finding could be generalized over the wider population. For instance, during the main study, several experiments were carried out with correlation and covariance checked through ANOVA analysis. This helped to determine the extent to which generalisabiliy could be spotted. The various statistical analyses are as depicted throughout Chapter 4. Extraneous variables and outside influences were hence controlled to avoid negative impact on research outcomes.

3.8.3 DATA ANALYSIS TOOLS AND TECHNIQUES

The study produced both quantitative and qualitative data, showing the various behavioural parameters for a human vehicle driver. Data analysis used quantitative techniques with the Microsoft Excel Application Software Package being used. The following tools and analysis techniques were employed in addition to specialized algorithms:

i) ANOVA analysis tools – These utilized the single factor and two-factor analysis tools in the determination of the fact that each sample was drawn from the same underlying probability distribution against the alternative hypothesis that underlying probability distributions are not the same for all samples. The tests were done at statistical significant levels of $p < 0.05$.

ii) Descriptive statistics analysis tool – Generated a report of univariate statistics for data in the input range for any given variables(s). It provided information about the central tendency and variability in the data including the mean, mode, standard deviation, kurtosis among others.

iii) Correlation and Covariance tools – Each tool gave an output matrix depicting the correlation coefficient or covariance, respectively, between each pair of measurement variables. The difference is that correlation coefficients are scaled to lie between -1 and +1 inclusive. Corresponding covariance are not scaled. Both the correlation coefficient and the covariance are measures of the extent to which two variables vary together.

3.8.4 DATA ANALYSIS ALGORITHMS

3.8.4.1 FORMULATION OF THE DRIVER BEHAVIOUR DATASET

The study relied on GPS data collected in realtime as drivers go along with their normal operations. The main parameter required for profiling drivers are speed, altitude, direction, timestamp and GPS signal strength data. These were complemented by proximity sensor data to take care of presence or absence of obstacles in the driving environment. Drivers' position in form of coordinates is essential for any detailed report. The study was limited to five main categories of driver behaviour: speeding, acceleration, deceleration, stopping and cornering. Table 3.6 outlines possible attributes per category.

Table 3.6. Categories of Driver Behaviour Attributes

Profile Category	Behavioural Attribute
Speeding	▪ Normal Speeding ▪ High Speeding
Acceleration	▪ Normal Acceleration ▪ Harsh Acceleration
Deceleration	▪ Normal Deceleration ▪ Harsh Deceleration
Stopping	▪ Normal Braking to Stop ▪ Harsh Braking to Stop
Cornering	▪ Normal Cornering ▪ Harsh Cornering

The study established no existence of world standard braking and acceleration metrics. However, some key metrics behind driver perception-reaction distance and braking distance leading to a realisation of the stopping sight distance were used in this regard. Stopping sight distance is the distance covered during two phases of stopping a vehicle: perception-reaction time (PRT), and maneuver time (MT) [78]. Perception-reaction time is the time taken for a driver to realize that a reaction is needed due to a given condition, decided what maneuver is appropriate (in this case, stopping the vehicle), and start the maneuver (taking the foot off the accelerator and depressing the brake pedal). On the other hand, maneuver time is the time taken to complete the maneuver (decelerating and coming to a stop). The distance driven during perception-reaction time and maneuver time is the sight distance needed. This may however vary due to the fact that different vehicle models from different manufactures have varied strengths and capabilities. For instance, some vehicles have a powerful braking system compared to others. Furthermore, other vehicles have greater power picking levels allowing instant speed shifts. The study used a braking and acceleration distance of less than 5 meters per square seconds to be normal. Any instances greater than this limit should hence be treated to be harsh acceleration or braking behaviour.

Speeding metric could be set to international or national standards. For instance, according to the Kenyan Traffic Act on speed limits, private motor vehicles are limited to 110km/h and 100km/h on dual-carriage highways and on single carriage highways respectively. On the other hand, commercial vehicles, passenger vehicles, omnibuses and other Public Service Vehicles are limited to 80 km/h on any type of road. Furthermore, speed limited zones require slightly low speed settings. For instance, built up area are always limited to maximum speeds of 50km/h regardless of type of road or vehicle.

3.8.4.2 DETERMINATION OF BEHAVIOUR AND ENVIRONMENT

The study employed graphical probabilistic models to establish the behaviour and the nature of operational environment based on possible probabilities given a set of variables. The study was limited to five GPS data variables and obstacle data: speed, direction, altitude, time, signal strength and obstacle presence signal. Two graphical models were considered: the Bayesian Network (BN) and the Dynamic Bayesian Network (DBN).

Bayesian Network

The Bayesian Network is a probabilistic graphical model, a type of statistical model that maps a set of variables and their conditional dependencies [79]. Figure 3.9 outlines a Bayesian Network composed of five variables: change in speed, altitude, direction, obstacle and the GPS signal strength. The time variable was incorporated in determining the various time slices in the DBN described in the next section. Hence, not represented as a variable in the BN.

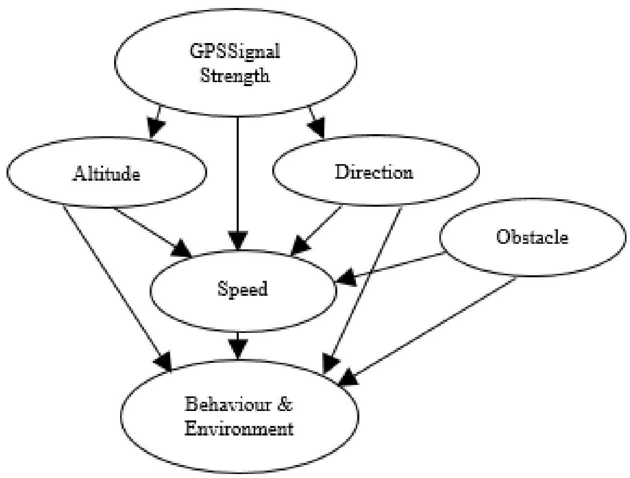


Figure 3.9. Bayesian Network of Five Variables

According to the graphical Bayesian Network in Figure 3.9, driver behaviour and nature of environment depend on change in speed, altitude, direction and presence or absence of obstacles. It is further evident that a change in speed is affected by changes in altitude and directions and presence or absence of obstacles. Furthermore, the GPS signal strength affects changes in altitude, speed and direction. The probabilities in the networks can be summarized as per equation (5).

$$P(\text{Behaviour \& Environment}) = P(\Delta\text{Altitude} \mid \text{GPSSignalStrength}) \cdot P(\text{Direction} \mid \text{GPSSignalStrength}) \cdot P(\text{Speed} \mid \text{Altitude, Direction, GPSSignalStrength, Obstacle}) \quad (5)$$

The possible observations were represented in two sets: driver behaviour and nature of the environment sets as shown in equation (6).

observations={

('normal_braking', 'harsh_braking', 'normal_acceleration', 'harsh_acceleration', 'normal_cornering', 'harsh_cornering', 'normal speeding', 'high speeding'),

('meander', 'straight', 'up-hill', 'down-hill')

} (6)

Dynamic Bayesian Network

Based on the dynamic natures of GPS data over time, it was necessary to consider the Dynamic Bayesian Network representation. A DBN is a Bayesian Network that relates variables over adjacent time steps [79]. It is hence often referred to as a 2-Time-slice Bayesian Networks (2TBN). According to the 2TBN, at any given time t, the value of a variable can be calculated from the internal regressors and immediate prior value at time t-1. In this case, the 2TBN could be represented as depicted in Figure 3.10.

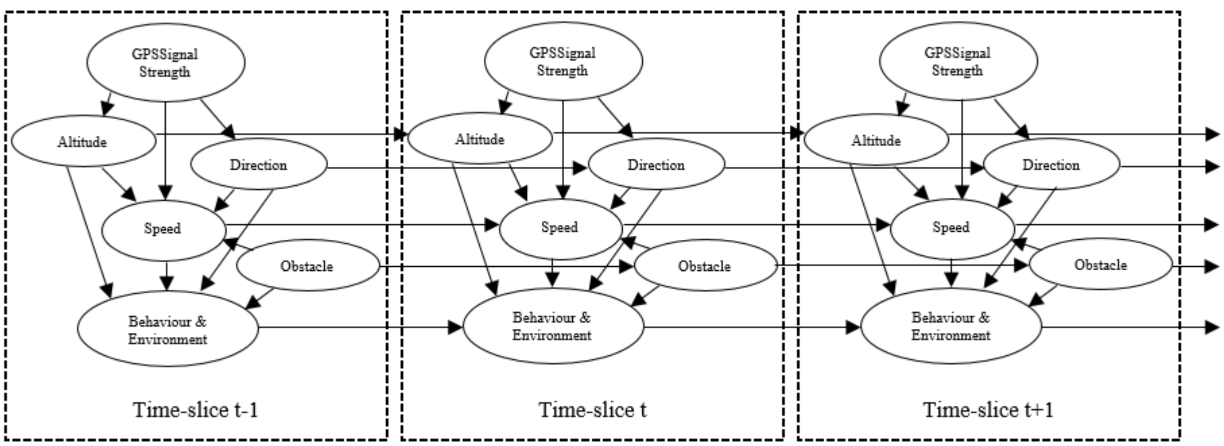


Figure 3.10. A 2TBN for Establishing Driver Behaviour and Operational Environment

The model in the figure represents three copies of time-slices where each time-slice is a Bayesian Network. According to the sample network, the probabilities for the three time-slices can be summarized by equation (7) to (9), where, the difference between time t and t-1 depends upon the time difference between two data points logged at the server.

$$P(Behaviour\ \&\ Environment_{t-1}) = P(Altitude_{t-1} \mid GPSSignalStrength_{t-1}) \,.\, P(Direction_{t-1} \mid GPSSignalStrength_{t-1}) \,.\, P\big(Speed_{t-1} \mid Altitude_{t-1}, Direction_{t-1}, Obstacle_{t-1}, GPSSignalStrength_{t-1}\big) \quad (7)$$

$$P(Behaviour \ \& \ Environment_t) = P(Altitude_t \mid Altitude_{t-1}, GPSSignalStrength_t) \ . \ P(Direction_t \mid Direction_{t-1}, GPSSignalStrength_t) \ . \ P(Speed_t \mid Speed_{t-1}, Altitude_t, Altitude_{t-1}, Direction_t, Direction_{t-1}, Obstacle_t, Obstacle_{t-1}, GPSSignalStrength_t) \tag{8}$$

$$P(Behaviour \ \& \ Environment_{t+1}) = P(Altitude_{t+1} \mid Altitude_t, GPSSignalStrength_{t+1}) \ . \ P(Direction_{t+1} \mid Direction_t, GPSSignalStrength_{t+1}) \ . \ P(Speed_{t+1} \mid Speed_t, Altitude_{t+1}, Altitude_t, Direction_{t+1}, Direction_t, Obstacle_{t+1}, Obstacle_t, GPSSignalStrength_{t+1}) \tag{9}$$

This means that as time progresses, a new time-slice is generated. In which case, the value of each of the five data variables is affected by the immediate previous value in the prior time-slice except for GPS Signal Strength variable. There can be as many time-slices as the number of times the change in time is recorded. This model is hence vital for mapping of GPS data since such an analysis is a time series kind of analysis. It should hence be noted that a different behaviour and environment is generated per time-slice. For effective driver profiling, an average of time-slice behaviours for a journey has to be determined.

Such a DBN is defined as a pair, (BN, BN'), where BN is a Bayesian Network which defines the prior $P(\lambda_1)$, and BN' is a 2TBN that defines $P(\lambda_t \mid \lambda_{t-1})$ by means of a directed acyclic graph. This is as summarised in (10). Da et al. [80] present a deeper elaboration of the Bayesian Network model's equation in a different way.

$$P(\lambda_t|\lambda_{t-1}) = \prod_{k=1}^{n} P(\lambda_t^k \,|\, \Pr(\lambda_t^k)) \tag{10}$$

Equation (4) is referred to as a chain rule, where at any given time t, λ^k_t is the k'th node while $\Pr(\lambda^k_t)$ are its parents in the graph. The nodes in the first slice of a 2TBN are not associated with any parameters while each node in the second slice onwards has an associated conditional probability distribution, hence for all times t greater than 1, we define $P(\lambda^k_t \mid \Pr(\lambda^k_t))$. It is worth noting that the parent of a node can either be in the same or previous time-slice. The complete joint distribution for j time-slices could hence be as defined in (11).

$$P(\lambda_{1:j}) = \prod_{t=1}^{j} \prod_{k=1}^{n} P(\lambda_t^k \,|\, \Pr(\lambda_t^k)) \tag{11}$$

3.8.4.3 POSSIBLE STATES WITH PROFILING PROBABILITIES

Each time-slice could fall under one of the n possible driver states as outlined in Table 0.1 under Appendix B, where n is total number of time-slices. The states have possible probabilities that the 2TBN could use to determine the behaviour and nature of the driver's environment. A 2TBN is a generalization of the Hidden Markov Model (HMM). Hence, HMM could be applied to the states outlined in the table to determine possible transitions and observation probabilities. However, this will result to a complex state diagram due to the high number of states and expected transition probabilities.

Any additions of variables to the states doubles or even triples the total number of probable states hence contributing to the complexity of the entire network. For instance, if we factor weather in the operational environment of the driver, then each of the current states will be duplicated to take care of dry or wet. The set of states will hence shift from 128 to 256 states hence complicating the environment further.

3.8.4.4 MACHINE LEARNING

This study started with supervised learning that entailed the use of training data that provided examples of situations each with outcomes that helped the machine, in this case the driver agent, to learn to predict outcomes of new data based on past examples. Validation and test data was then used to refine and gauge the performance of the agent. Reinforcement learning in form of rewards was involved to enable the machine to determine correct decisions made.

For effective machine learning, a huge set of data was collected from different environments and drivers. Data for the 30 drivers whose maximum acceleration and deceleration margins were within acceptable range of -5 to +5 m/s^2 and whose driving speeds were less than or equals to 80 km/h or 100 km/h for Public Service Vehicles and Private Service Vehicles respectively was considered for training, validation and testing of the agent. A compromise was however made for instances here highest speeds did not exceed 5 km/h above the recommended speeds. The data collected was divided into three sets: Training, validation and testing sets to serve the various purposes for preparations of the driver agent.

A. Training Set

The training set was used for teaching the driver agent based on behavioural action patterns of a human vehicle driver. This acted as a supervised learning paradigm. This approach employed regression models over a time series as supervised learning algorithms. The 2TBN described in the previous section was used as a representative of both an ensemble and time series algorithm. The learning was probabilistic over a series of time.

The approach used first subjected drivers to drive tests as their behaviour was recorded. Data for drivers with a commendable behaviour was used to build the training dataset for the agent. Commendable behaviour in this case was determined by the level of consistency in behavioural pattern. The training was done in such a manner that as a driver makes a real road trip, raw data was captured and stored in the database. At the same time, automatic data pre-processing was occurring behind the scenes to extract and log the following data parameters in a knowledge base:

i) Latitude and Longitude
ii) Changes in speed
iii) Changes in time
iv) Changes in altitude
v) Changes in direction
vi) Average normal and harsh acceleration
vii) Average normal and harsh braking
viii) Average normal and harsh cornering
ix) Average straightness and meandering
x) Average uphill and downhill stretches

Each data point recorded in the knowledge base formed a Gaussian with the coordinates forming the central point of the Gaussian. A single data point is composed of five to ten averaged human vehicle driver behavioural data within the region forming the Gaussian. In this case, several Gaussians are formulated as the training knowledge base is being formulated for a given road segment. The Gaussians could be independent as some may overlap at different rates as shown in

Figure 3.11. The only limitations of this approach is the fact that all the Gaussians are formulated with a similar radius hence they all form regions with equal perimeters.

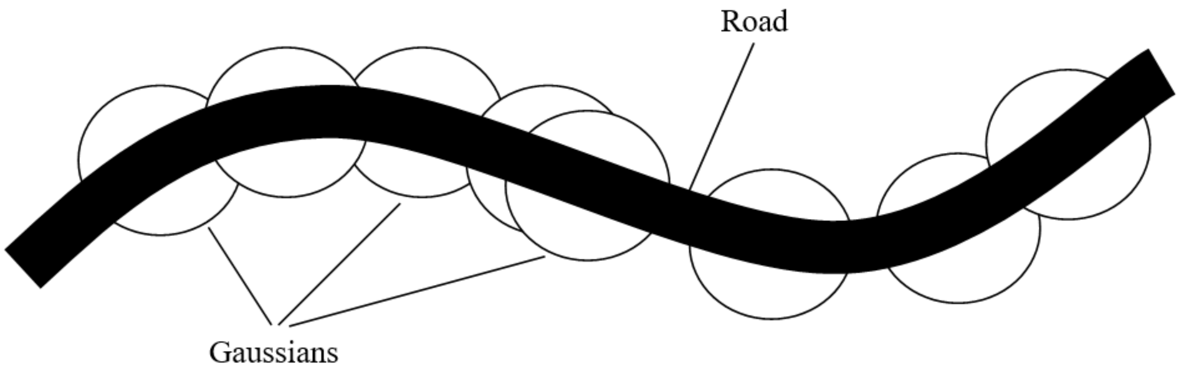


Figure 3.11. Road Segment with Gaussians

The agent was then subjected to the data in the knowledge base to ascertain its actions in comparison to actual driver actions in realtime. A commendable success rate was awarded a reward as a sign to show that the agent got it right and that such actions have a positive impact in future. For future analysis of the agent's behaviour, all its actions were logged in another dataset used during the validation phase.

B. Validation Set

After learning, the validation data set was then used to give an estimate of model skill while tuning the model's hyper parameters. This provided an unbiased evaluation of the agent on the training dataset.

C. Test Set

The agent's subsequent actions under dynamic conditions were then evaluated against sets of performance standards using the test dataset. These performance standard were determined by the thresholds for each of the behavioural categories as outlined in section 4.3.1 Table 4.15. The dataset provided an unbiased evaluation of the final model fit on the training dataset. A reward for best actions was issued in form of points and badges as a reinforcement kind of learning paradigm.

Based on the nature of GPS data, supervised learning best fits since specific outcomes can be deduced from example data. In this respect, probabilistic reasoning techniques that involve Bayesian inferencing, mixture models, time series analysis, factor analysis and expectation maximisation were used.

Probabilistic Reasoning Methodologies

Based on the stochastic nature of the driving environment, the intelligent agent relied on probabilistic reasoning methodologies for both qualitative and quantitative analysis. The algorithms behind the driver agent's performance hence used probabilistic methodologies that include Mixture models and Bayesian inferencing techniques for data analysis to facilitate effective driver behaviour pattern recognition and matching. Factor Analysis statistically described variability among observed, correlated variables. To effectively implement maximum likelihood estimations for any given parameters, the Expectation Maximisation (EM) algorithm was used as a soft K-Means clustering algorithm for determination of parameters of a mixture with priorities given on number of components.

i) Factor Analysis

Factor analysis is a correlational technique used to find and describe underlying factors driving outcome for a set of variables. The analysis targets to get the variance or covariance between the observed variable in a population by a set of fewer unobserved factors and weightings. The ANOVA single factor analysis was used to ascertain consistency in speeding, acceleration, deceleration, cornering and stopping patterns, where random groups of experiments were analysed over a control group.

To determine driver behaviour, the study employed factor analysis based primarily on two observed GPS variables, namely, speed and angle. Changes in speed determined acceleration, deceleration and stopping patterns as unobserved factors over time and good GPS signal strength. On the other hand, angle changes determined cornering patterns as unobserved factors.

To determine the operational environment, factor analysis was founded on observed GPS angle and altitude variables. The road pattern was determined by changes in direction based on GPS angle variable over time and good GPS signal strength. On the other hand, road terrain was determined by changes in altitude over time and good GPS signal strength.

The comparative analysis of observed speed, altitude and angle variable data was used in the determination of cornering trends, road terrain and road pattern as unobserved factors. All these unobserved factors cumulatively led to the determination of a vehicle driver's behaviour hence the formulation of the driver bahaviour dataset.

ii) Mixture Models

Mixture models are probabilistic sound ways of clustering, mostly soft clustering. Each cluster in a mixture model corresponds to a probability distribution. The aim was to discover parameters of each distribution, for instance, the mean and covariance of each distribution. The study used Gaussian Mixture Models (GMM) with the Expectation Maximisation (EM) algorithm for point assignment and Gaussian adjustment as follows:

a) Gaussian Mixture Models

The Gaussian Mixture Model (GMM) is a type of Mixture Model that clusters models as Gaussian distributions and not just by their means. The GMM allows for formulation of more than one cluster. The clusters could even overlap. To position data points to appropriate clusters, the Expectation Maximisation algorithm was used since it uses probabilities as opposed to the K-means that heavily rely on means.

Figure 3.12 outlines an example of a Gaussian Mixture Model with two overlapping Gaussians. Based on the model, each data point was positioned to either Gaussian using probabilities. In such cases, the log likelihood is heavily used in the determinations of the probabilities. This is achieved using the Expectations Maximisation algorithm.

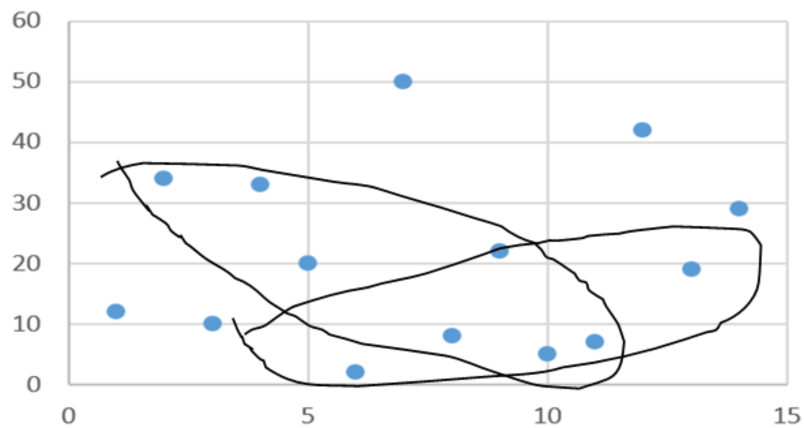


Figure 3.12. Example of a Gaussian Distribution

b) Expectation Maximisation

The Expectation Maximisation (EM) is a probabilistic distribution algorithm that allows for automatic inferencing of parameter values in a mixture model. The algorithm places Gaussians randomly by means and variances. For each point, EM tries to look for the probability of the cluster it falls under. It then adjusts and fits points assigned to the various Gaussians. This is iterated until convergence. The Expectation Maximisation is a soft clustering technique as opposed to the K-means that uses hard clustering.

The study employed the GMM and EM in the determination of possible actions that the driver agent could take. This came handy in machine learning for pattern determination in the training dataset. Furthermore, they were applied in validation and testing of the driver agent model. For instance, the agent determined whether to accelerate, decelerate, stop or turn based on positions of detectable features and other agents within its environment. In such cases, one or more Gaussians are virtually established hence rendering detected features to have probabilities that distribute them among the Gaussians. These probabilities are established using the Expectation Maximisation algorithm based on the log likelihood. As the agent moves, Gaussians keep shifting positions based on the new detectable features as new probabilities keep being generated.

iii) Bayesian Inferencing

The Dynamic Bayesian Network described in section 3.8.4.2 was also applied in machine learning. The 2TBN technique used incorporated factor analysis.

iv) Decision Trees

Some instances used decision tree in the determination of actions to be performed by the driver agent. Decision Tress were used in form of conditional control statements. They were heavily relied upon in the identification of strategies likely to reach goals. For instance, the determination of driver behaviour used the 2TBN implemented as Decision Trees using the if … else conditional statement in the algorithm logic. Decision Tress further complemented Mixture Models in machine learning for driver agent training, validation and testing.

3.8.4.5 AGENT EVALUATION METRICS FOR PERFORMANCE PARAMETERS

To realise the five behavioural parameters: speeding, acceleration; deceleration; cornering; and stopping trends, it was necessary to understand key metrics behind driver perception-reaction distance and braking distance that lead to a realisation of the stopping sight distance. Stopping sight distance is the distance covered during two phases of stopping a vehicle: perception-reaction time (PRT), and maneuver time (MT) [78]. Perception-reaction time is the time taken for a driver to realize that a reaction is needed due to a given condition, decided what maneuver is appropriate (in this case, stopping the vehicle), and start the maneuver (taking the foot off the accelerator and depressing the brake pedal). On the other hand, maneuver time is the time taken to complete the maneuver (decelerating and coming to a stop). The distance driven during perception-reaction time and maneuver time is the sight distance needed. Hence, the agent's perception-reaction distance was computed using equation (12) and (13).

$$d_{PRT} = 0.278\ Vt\ \text{(Metric)} \tag{12}$$

$$d_{PRT} = 1.47\ Vt\ \text{(US Customary)} \tag{13}$$

Where:

d_{PRT} = driver perception-reaction distance, m (ft)

V = design or initial speed, km/h (mph)

t = brake reaction time, in seconds

Based on different study results, 2.5 seconds has been chosen for a perception-reaction time which accommodates approximately 90% of drivers when confronted with simple to moderately complex situations [78]. For more complex cases, greater reaction time should be expected.

Braking Distance

Braking distance was based on equation (14) and (15)

$$d_{MT} = 0.039\ V^2/a \text{ (Metric)} \tag{14}$$

$$d_{MT} >= 1.075\ V^2/a \text{ (US Customary)} \tag{15}$$

Where:

d_{MT} = braking distance, m (ft)

V = design or initial speed, km/h (mph)

a = deceleration rate, m/s^2 (ft/s^2)

Actual braking distances are affected by the vehicle type and condition, the original speed, the incline of the road, the road surface, and numerous other factors. A deceleration rate of 3.4 m/s^2 is used to determine stopping sight distance with approximately 90% of drivers experiencing decelerations at rates greater than that [78]. These values are within most drivers' ability to stay within the lane and maintain steering control. It should be noted that most wet road surfaces and most vehicle braking systems are capable of providing enough braking force to exceed this deceleration rate.

Stopping Sight Distance (SSD)

Stopping sight distance is hence the sum of reaction distance and braking distance as depicted in equation (16) to (18)

$$SSD = d_{PRT} + d_{MT} \tag{16}$$

$$SSD = 0.278\ Vt + (0.039\ V^2)/a \text{ (Metric)} \tag{17}$$

$$SSD = 1.47\ Vt + (1.075\ V^2)/a \text{ (US Customary)} \tag{18}$$

Proper performance of the driver agent was depended on a number of factors. Based on the description of the stopping sight distance, the driving speed and time emerge to be key variables in the determination of driver behavioural patterns. Fortunately, speed and time are data parameters supplied by the type of GPS receivers used in this study. Data for obstacles in sight of the driver was supplied proximity sensors through a Data Collection Unit interfaced to the GPS receiver.

The research sought to formulate, implement and evaluate the effectiveness of a utility-based driver agent that models a human vehicle driver's behaviour under diverse conditions. Data was collected in real-time using the GPS system. The system comprised GPS satellites, GPS receivers, and a server. GPS receivers continuously acquired GPS data from GPS satellites. The data was then relayed to the server via GPRS. GPS receiver's data was complemented with proximity sensor's obstacle data from a custom-made Data Collection Unit (DCU).

The data collected by the system led to the formulation of a driver behaviour dataset that was then subjected to a driver agent through three main stages: training, validation and testing. The agent acted as a utility-based driver running in parallel with a human driver without activating mechanical actuators. It instead operated as a software agent with screen display of actions. The agent's performance measures were limited to: speeding; acceleration; deceleration; cornering and stopping trends and detection of road terrain and road pattern achieved through probabilistic reasoning. Hence, stochastic methodologies that include Mixture Models with Bayesian inference techniques were used for effective driver behaviour pattern recognition and matching. The study was based on a target sample of 30 drivers subjected to instrumented vehicles comprising of two private cars and fifteen Public Service Vehicles.

3.9 SUMMARY

The chapter discussed the research design and methodology, outlining the theoretical and conceptual frameworks, data collection process, data analysis and presentation, validity and reliability of the data collection instruments and analysis techniques used. The next chapter brings out study results and their discussion.

CHAPTER 4
RESULTS AND DISCUSSIONS

This chapter presents study findings and their discussion for both the prestudy and the main study. Main study results and their discussion are presented with respect to the study objectives. The chapter concludes with a summary of the findings with respect to the study objectives, research questions and the hypothesis.

4.1 PRESTUDY RESULTS

A prestudy was carried out at the initial phase of the research as a form of validation for both the data collection tools, the independent variables and algorithms behind data analysis and consistency in data collection and analysis. Several tests were done during the prestudy.

4.1.1 VALIDITY OF DATA COLLECTION TOOLS AND METHODS

The following analysis covers one of the prestudy tests as an indicator of how the entire model ought to function towards achieving the research objectives.

4.1.1.1 BAYESIAN NETWORK ANALYSIS

Experiments were carried out considering both strata and different road segments. A sample of these experiments is as outlined in Figure 4.1, with data in Appendix D, Table 0.2, during which 277 data points were logged at the GPS server. The experiment was carried out on a half-dual and half-single carriageway road segment whose route map is as shown in Figure 4.1. The road segment was composed of relatively straight stretches with few clear corners, some of which are controlled by roundabouts. The road terrain was relatively flat with gentle slops at some point and a steep slope over a very short stretch. Other factors included daytime, dry weather, a mixture of both built-up and nonbuilt-up sections. Figure 4.2 – 4.7 outlines summaries of experiment results.

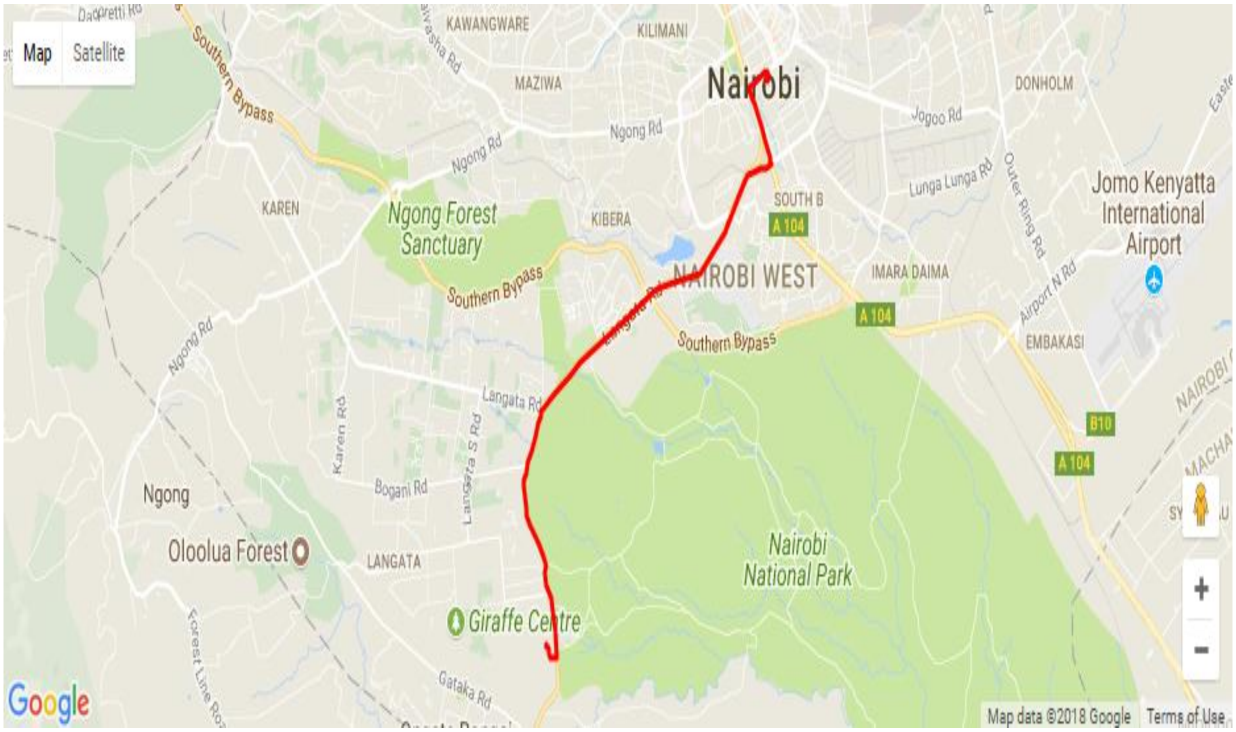


Figure 4.1. Sample Half-Dual and Half-Single Carriageway

Analysis of Data Patterns

Considering graphical analysis outlined in Figures 4.2 – 4.6, promising data for speed, altitude, direction and GPS Signal were collected.

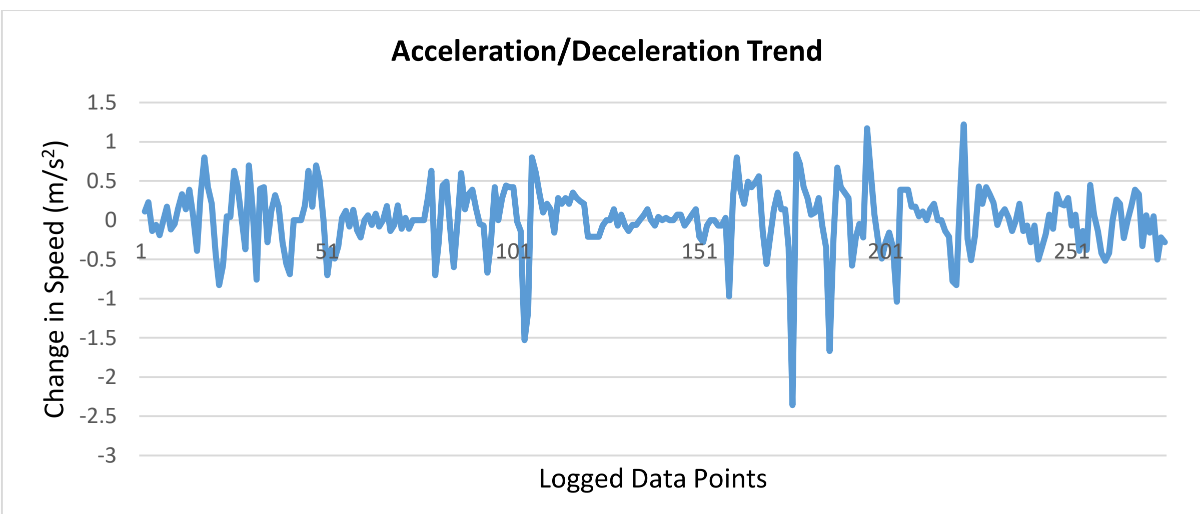


Figure 4.2. Patterns for Acceleration and Deceleration

Acceleration and deceleration patterns depend on changes in speed. Such patterns are vital in the determination of normal or harsh acceleration and deceleration behaviour. Based on the patterns, the driver had behavioural patterns within a normal range. It should be noted that the study used an acceleration and deceleration margin of less than or equal to 5 m/s^2 to be normal. Any instances greater than this limit are treated as harsh acceleration or deceleration behaviour. Based on the results shown in Figure 4.2, none of the changes in acceleration exceeded 5 m/s^2, depicting normal driving behaviour.

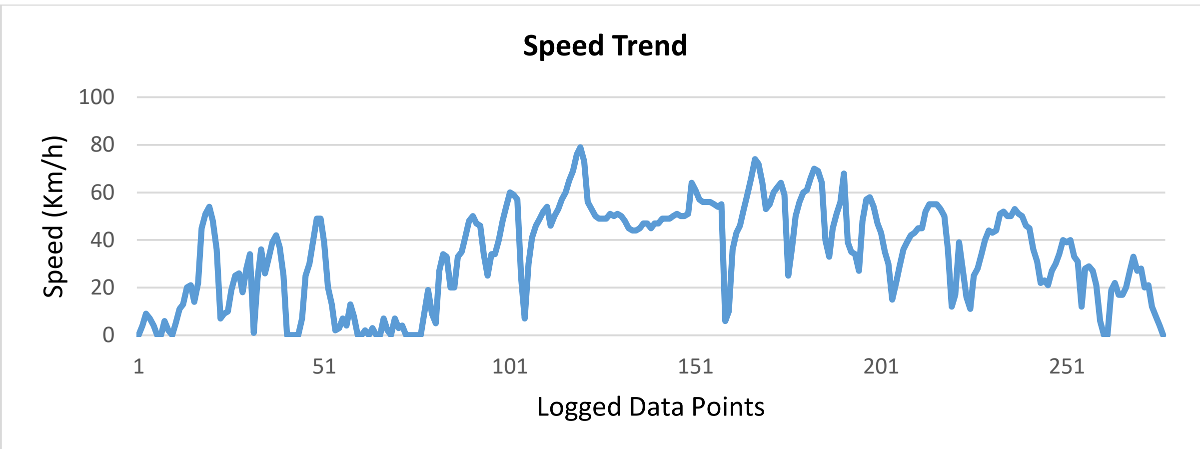


Figure 4.3. Patterns for Speed Changes

Speed patterns help in the determination of speeding behaviour centered on preset speed limits per road or vehicle type. Based on the results in Figure 4.3, the driver had speeds below 100 km/h, which was acceptable for the test road and vehicle type. This was a significance of normal speeding behaviour.

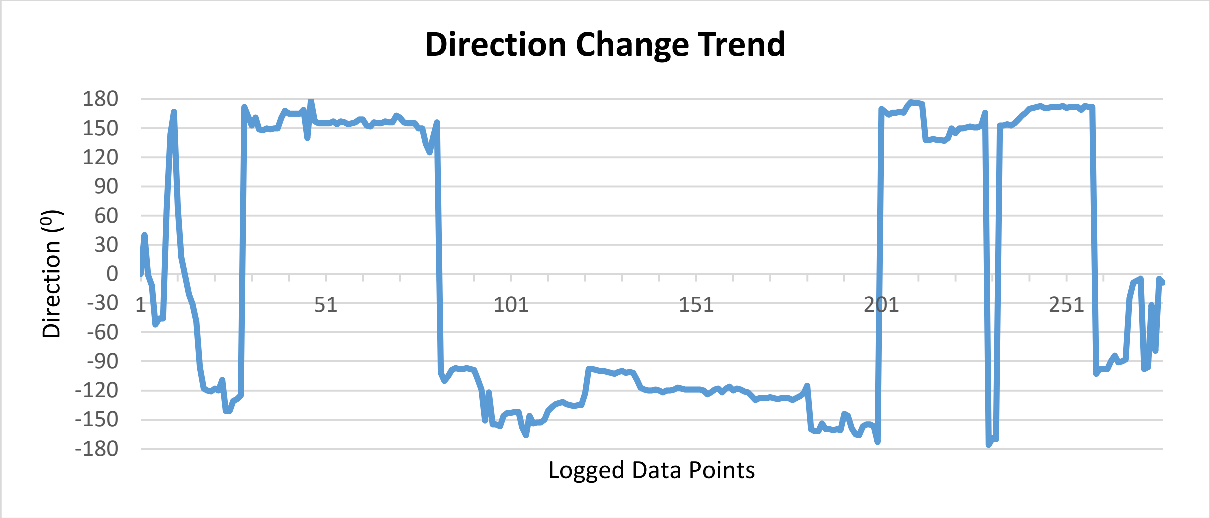


Figure 4.4. Patterns for Direction Changes

The study employed a GPS receiver that transmits data with an angle parameter whose value ranges from 0 – 360 degrees. This is used to determine the direction that the vehicle is headed centered on compass points where $0^0/360^0$, 45^0, 90^0, 180^0 and 270^0 signify North, East, South and West respectively. The value was critical in the determination of road patterns, which was in turn useful for establishment of cornering effects based on changes in the angle reading. Figure 4.4 shows the direction change trends where the values on the y axis could be interpreted as follows:

- N: 0
- NE: 1 – 89
- E: 90
- SE: 91 – 179
- S: 180 and -180
- NW: -1 – -89
- W: -90
- SW: -91 – -179

Based on the results in Figure 4.4, the trip had sharp shifts in values at the beginning and towards the end of the journey, a significance of sharp corners. The rest of the journey had relatively small changes in direction values, an indicator of smooth changes in directions. Most of the journey was headed towards the South, South East to be precise. The results match appropriately with the route as traced in the map in Figure 4.1. This acts as a good prove on validity of data collection tools.

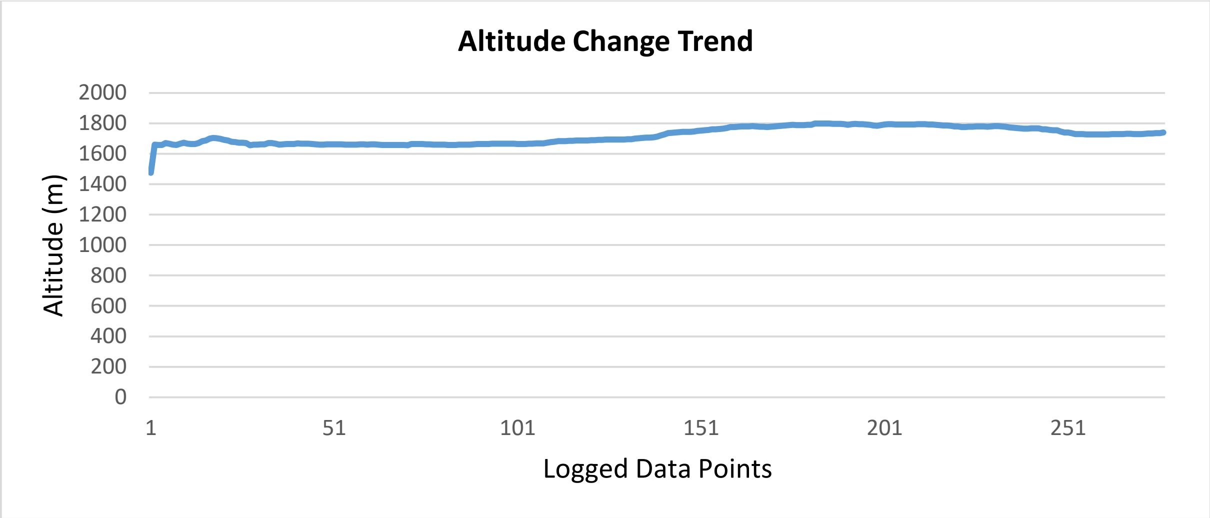


Figure 4.5. Patterns for Altitude Changes

Altitude signifies the height above sea levels. The value, expressed in meters is critical in the determination of road terrains. Hill climbing and rolling patterns could be represented by increase or decrease in altitude values respectively. Flat terrains are signified by constant altitude values hence gentle and steep levels depend on the magnitude of altitude changes. The results in Figure 4.5 depict a road that is relatively flat.

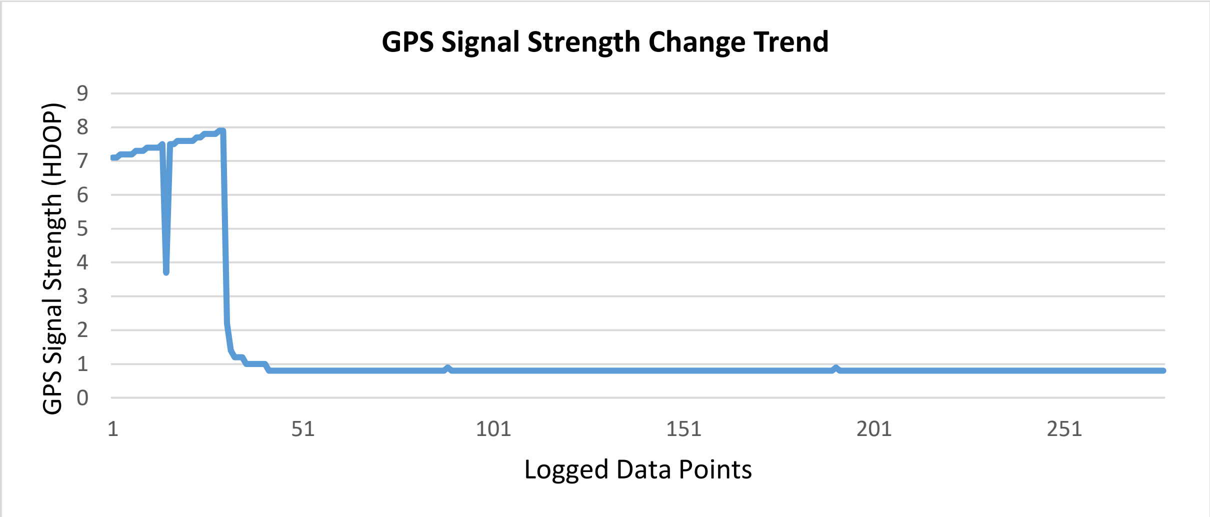


Figure 4.6. Patterns for GPS Signal Strength

GPS signal strength is a horizontal dilution of precision (HDOP) value. HDOP is a measure of the geometric quality of a GPS satellite configuration in the sky. It is a major factor in determining the relative accuracy of a horizontal position for a GPS receiver. The smaller the

DOP number, the better the geometry. HDOP values less than 5 indicate a relatively good signal. For instance, based on experiment results, the test experienced HDOP readings averaging to approximately 0.8 after poor signal strengths for the first 31 data points. Hence, good GPS signal strengths were recorded for the greater part of the journey as depicted in Figure 4.6. The major shifts in the beginning of the trip occurred at the point when the signal strength was yet to stabilize.

4.1.1.2 DBN BEHAVIOURAL ATTRIBUTES' PROBABILITIES

The 2TBN for the entire journey as highlighted in Figure 4.1 would lead to 277 different time-slices each with its own behavioural and environmental probabilities. This is due to the fact that the journey recorded 277 different data points at progressing times but with varied time intervals. Table 4.1 depicts sample data for the data points 45 to 60 for the journey with raw values from the GPS receiver being latitude, longitude, speed, altitude, direction, gpstime and GPS signal. The rest of the data values are computed to help subject them to the Bayesian Network. Each row in the table represents a single time-slice. In this case, the 2TBN hence has a total of 15 time-slices.

Table 4.1. Sample Data for the Journey

Data Point	Lat	Lon	Speed (km/h)	Altitude	Dir (º)	GPSTime	GPS Signal	Speed (m/s)	ΔSpd (m/s^2)	ΔDir (º)	ΔAlt (m)	ΔTime (s)	Accl/ Deccl (m/s^2)
45	-1.299307	36.824097	7	1663	169	1516346394	0.8	1.94	1.94	4	-3.9	10	0.19
46	-1.299643	36.824242	25	1661.6	140	1516346402	0.8	6.94	5	-29	-1.4	8	0.63
47	-1.300125	36.824371	30	1660.1	179	1516346410	0.8	8.33	1.39	39	-1.5	8	0.17
48	-1.300463	36.824474	40	1660.3	157	1516346414	0.8	11.11	2.78	-22	0.2	4	0.7
49	-1.300983	36.824711	49	1661.1	155	1516346419	0.8	13.61	2.5	-2	0.8	5	0.5
50	-1.301447	36.824932	49	1661.2	155	1516346423	0.8	13.61	0	0	0.1	4	0
51	-1.30183	36.825108	39	1662.6	155	1516346427	0.8	10.83	-2.78	0	1.4	4	-0.7
52	-1.302402	36.825378	20	1661.8	155	1516346441	0.8	5.56	-5.27	0	-0.8	14	-0.38
53	-1.302548	36.825447	13	1661.6	157	1516346445	0.8	3.61	-1.95	2	-0.2	4	-0.49
54	-1.30269	36.825508	2	1660.8	154	1516346454	0.8	0.56	-3.05	-3	-0.8	9	-0.34
55	-1.302808	36.825565	3	1660	157	1516346464	0.8	0.83	0.27	3	-0.8	10	0.03
56	-1.302878	36.825596	7	1660.1	156	1516346473	0.8	1.94	1.11	-1	0.1	9	0.12
57	-1.303087	36.825691	4	1660.7	154	1516346484	0.8	1.11	-0.83	-2	0.6	11	-0.08
58	-1.30335	36.825794	13	1661.5	155	1516346503	0.8	3.61	2.5	1	0.8	19	0.13
59	-1.303622	36.825932	8	1661.4	156	1516346514	0.8	2.22	-1.39	1	-0.1	11	-0.13
60	-1.303683	36.825958	0	1660.5	159	1516346524	0.8	0	-2.22	3	-0.9	10	-0.22

4.1.1.3 SAMPLE DRIVER BEHAVIOUR ANALYSIS

Table 4.2 shows an analysis of probabilities of driver behaviour and nature of operational environment for the road segment highlighted in Figure 4.1. Individual time-slice behavioural and environmental probabilities were established based on changes in altitude, direction, speed and time as outlined in Table 4.1 against the state probabilities in Table 0.1. Hence, the state column in Table 4.2 matches each time-slice with its respective state in Table 0.1. The profiling engine could generate an average for the entire journey based on individual time-slice probabilities established by the Bayesian Network to generate a full driver profile.

Table 4.2. Driver Behaviour and Operational Environment Probabilities per Time-slice

Time-slice	**State (Table 0.1)**	**Behaviour**						**Environment**			
		Normal Acceleration	**Harsh Acceleration**	**Normal Braking**	**Harsh Braking**	**Normal Cornering**	**Harsh Cornering**	**Meander**	**Straight**	**Up-Hill**	**Down-Hill**
45	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil	Nil
46	26	0.28	0.07	0.28	0.07	0.15	0.15	0.10	0.40	0.10	0.40
47	26	0.28	0.07	0.28	0.07	0.15	0.15	0.10	0.40	0.10	0.40
48	2	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.40	0.10
49	2	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.40	0.10
50	2	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.40	0.10
51	66	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.40	0.10
52	122	0.15	0.20	0.15	0.20	0.15	0.15	0.10	0.40	0.10	0.40
53	74	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.10	0.40
54	90	0.30	0.05	0.30	0.05	0.15	0.15	0.10	0.40	0.10	0.40
55	26	0.28	0.07	0.28	0.07	0.15	0.15	0.10	0.40	0.10	0.40
56	18	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.40	0.10
57	82	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.40	0.10
58	18	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.40	0.10
59	90	0.30	0.05	0.30	0.05	0.15	0.15	0.10	0.40	0.10	0.40
60	90	0.30	0.05	0.30	0.05	0.15	0.15	0.10	0.40	0.10	0.40
Average Probability		**0.25**	**0.10**	**0.25**	**0.10**	**0.15**	**0.15**	**0.10**	**0.40**	**0.24**	**0.26**

The same approach could be subjected to the entire journey with probabilities of driver behaviour and nature of operational environment being determined for all the 277 time-slices. The resulting average probabilities would reflect the driver behaviour and operational environment for the entire journey. The results are an indicator that the 2TBN is suitable for analysis of data towards determination of driver behaviour.

4.1.1.4 VALIDITY OF DATA COLLECTION TOOLS AND METHODS

To validate data collection tools for consistency, the ANOVA single factor analysis was employed. ANOVA was chosen in this case since it is a collection of statistical models and their associated estimations used to analyse the differences among group means in a sample. The single factor analysis was used since the analysis in this case was based on speed as the main independent variable over a set of four drivers. This was done for four drivers operating on the same road as outlined in Table 4.3 to Table 4.4.

Table 4.3. Descriptive Statistics

	Speed (D1)	*Speed (D2)*	*Speed (D3)*	*Speed (D4)*
Mean	34.33576642	35.27007299	27.59854	32.26277372
Standard Error	1.551958187	1.437494886	1.843154	1.454817956
Median	34	34	26	36
Mode	28	29	0	45
Standard Deviation	18.16520485	16.82544626	21.57356	17.0282076
Sample Variance	329.9746672	283.0956419	465.4185	289.959854
Kurtosis	-0.32919918	-0.245092421	-1.16875	-1.02327068
Skewness	0.294212974	0.178519441	0.20055	-0.3020562
Range	84	77	79	64
Minimum	0	0	0	0
Maximum	84	77	79	64
Sum	4704	4832	3781	4420
Count	137	137	137	137
Confidence Level(95.0%)	3.069091637	2.842733503	3.644948	2.876990927

According to the descriptive statistics outlined in Table 4.3, three out of the four drivers had moderate positive skews in their driving speeds while one of the drivers had a moderate negative skew. All the drivers had platykurtic, since they all had values in the negative range. This signifies a flatter kind of distribution curve, hence, fewer or less outliers.

Table 4.4. ANOVA Single Factor Analysis

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4802.254	3	1600.751	4.679	0.003	2.621
Within Groups	186109.022	544	342.112			
Total	190911.276	547				

Based on the ANOVA single factor results outlined in Table 4.4 and in relation to the null hypothesis that states that the mean driving speed values of 4 different drivers are equal, since the p-value is 0.003, which is less than the significance level of 0.05, we reject the null hypothesis. This leads to the conclusion that some of the drivers have different driving speed means. The fact that the F value is greater than F critical value, it is just an indicator that something is significant in the results. This is the reality since human beings have different behaviours that will definitely translate to differences in driving speed. This could further be justified by Table 4.5 and Table 4.6 correlation and covariance results respectively that clearly show the correlations and variances in speeding behaviour.

Table 4.5. Correlation Analysis

	Speed (D1)	*Speed (D2)*	*Speed (D3)*	*Speed (D4)*
Speed (D1)	1			
Speed (D2)	0.240422521	1		
Speed (D3)	0.185235685	0.315943681	1	
Speed (D4)	0.014498375	0.252875219	0.215458	1

Table 4.6. Covariance Analysis

	Speed (D1)	*Speed (D2)*	*Speed (D3)*	*Speed (D4)*
Speed (D1)	327.566093			
Speed (D2)	72.94581491	281.0292504		
Speed (D3)	72.06180404	113.8456497	462.0213117	
Speed (D4)	4.451915392	71.92173264	78.57264638	287.8434

In summary, the study tested reliability as follows:

1. Test retest reliability

   A correlation of a set of human drivers and the agent subjected to a test on a similar road segment twice was done in order to evaluate stability over time.

2. Parallel forms reliability

   A correlation of a similar set of human drivers and the agent subjected to different road segments was done in order to evaluate consistency of results.

3. Internal consistency reliability

   This test complemented test retest and parallel form reliability tests. It was achieved through following methods:

   i) Average inter-item correlation

      An average correlation of coefficients of pairs of behavioural parameters was examined.

   ii) Split-half reliability

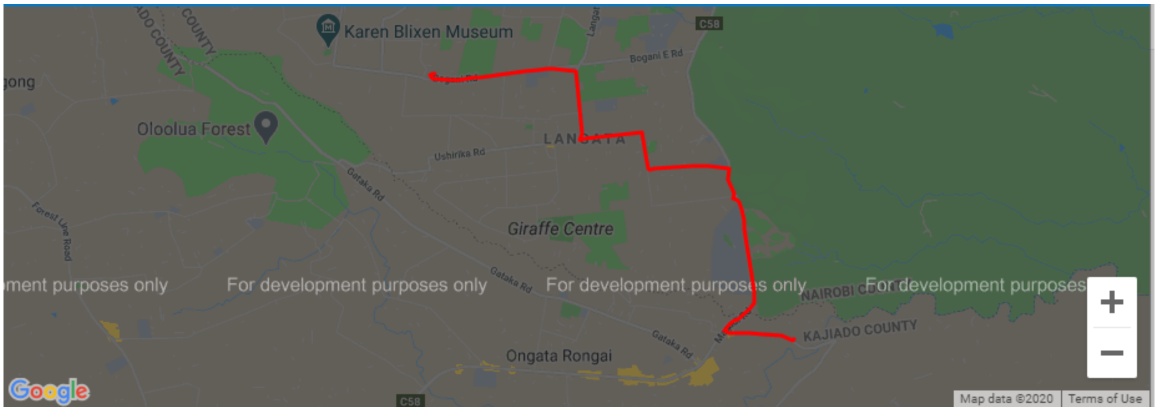
      Driver groups, behavioural parameters and/or test domains was split into halves then subjected to tests with the correlation between the two total set scores being determined.

4.1.2 DATA CONSISTENCY (RESULTS WITHOUT OBSTACLE SENSORS)

A further prestudy test involved experiments relying on GPS data variables only, without obstacle data. This was in a move to ascertain the effectiveness of GPS data only in driver behaviour analysis. The experiments further explored whether these data alone could inform successful modelling of vehicle driver agent.

4.1.2.1 EXPERIMENT DESCRIPTION

The 2TBN probabilities in Table 0.1 were implemented in form of an algorithm for the driver behaviour analysis system. A driver was monitored on different occasions and road segments. The study first explored the driver's behaviour on three different days, similar road segment, driving in the same direction, almost same times of the day. Sample data for one of the three experiments is as shown in Table 0.3 in Appendix D. The experiment was carried out on a single carriageway road segment as shown in the route map in Figure 4.7. The road segment composed of relatively straight stretches but with few sharp corners. The road terrain had relatively long flat stretches with a short steep hill at one point. Other factors included morning hours, dry weather, and busy road.



REG. NO.	GPSTIME	CHGACCL	CHGTIME	CHGALT	CHGDIR	ACCEL	BRAKING	CORNERING	TERRAIN	PATTERN
Sample	08:09:14	0.07	8	-0.6	-1	0.3	0.27	Corner 0.15	DownHill 0.4	Straight 0.4
Sample	2018-05-21 08:09:26	-0.32	12	7.1	-26	Norm Accl 0.25	Norm Brake 0.25	Norm/Harsh Corner 0.15	UpHill 0.5	Straight 0.4
Sample	2018-05-21 08:09:40	-0.32	14	3.5	-246	Norm Accl 0.2	Norm Brake 0.2	Harsh Corner 0.2	UpHill 0.4	Meander 0.4
Sample	2018-05-21 08:09:58	-0.29	18	-4.5	81	Norm Accl 0.25	Norm Brake 0.25	Harsh Corner 0.2	DownHill 0.4	Meander 0.4
Sample	2018-05-21 08:20:56	0	658	-0.2	170	Norm/Harsh Accl 0	Norm/Harsh Brake 0	Norm/Harsh Corner 0	UpHill/DownHill 0	Meander/Straight 0
AVERAGE						Norm :0.22 Harsh :0.1	Norm :0.2 Harsh :0.12	Norm :0.13 Harsh :0.14	Uphill :0.28 DownHill :0.17	Straight :0.33 Meander :0.12

Figure 4.7. Sample Single Carriageway (Prestudy)

The results for the experiment included a summary of the driver behaviour for the analysis period. This was founded on the 2TBN algorithm as discussed in section 3.8.4.2. The analysis shows a snapshot of the driver behaviour based on speeding, acceleration, braking and cornering patterns. The analysis indicates driving styles in form of probabilities of normal versus harsh behaviours. A higher probability is an indicator for the driver’s behaviour for the analysis item. It further determines the driver’s operational environment centered on the road terrain and road pattern. The terrain is expressed based on probability of uphill or downhill movements. The item with the highest probability value determines the nature of the road terrain for the given road segment. The same applies to the road pattern that is viewed from two perspectives, namely, straight or meander.

Analysis of Data Patterns

Considering graphical analysis outlined in Figure 4.8 – 4.12, good data for speed, altitude, direction and GPS Signal were collected. Good GPS signal strengths were recorded for the greater part of the journey.

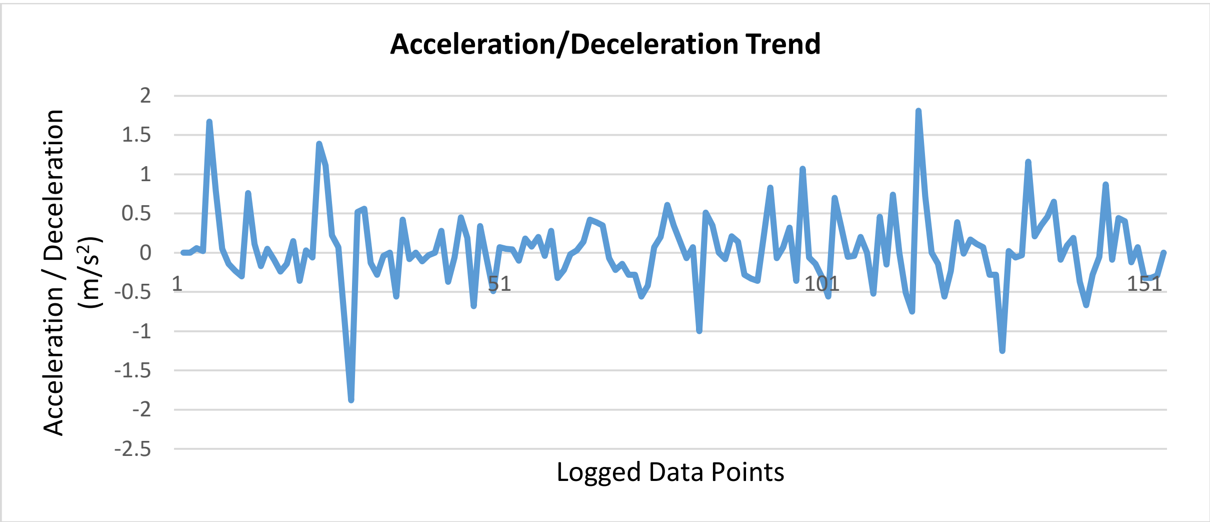


Figure 4.8. Patterns for Acceleration and Deceleration

Based on the patterns in Figure 4.8, the driver had acceleration and deceleration patterns within a normal range. It should be noted that the study used an acceleration and deceleration less than or equal to 5 m/s^2 to be normal, otherwise, treated as harsh acceleration or deceleration behaviour. Based on the results, none of the changes in acceleration exceeded 5 m/s^2, depicting normal driving behaviour.

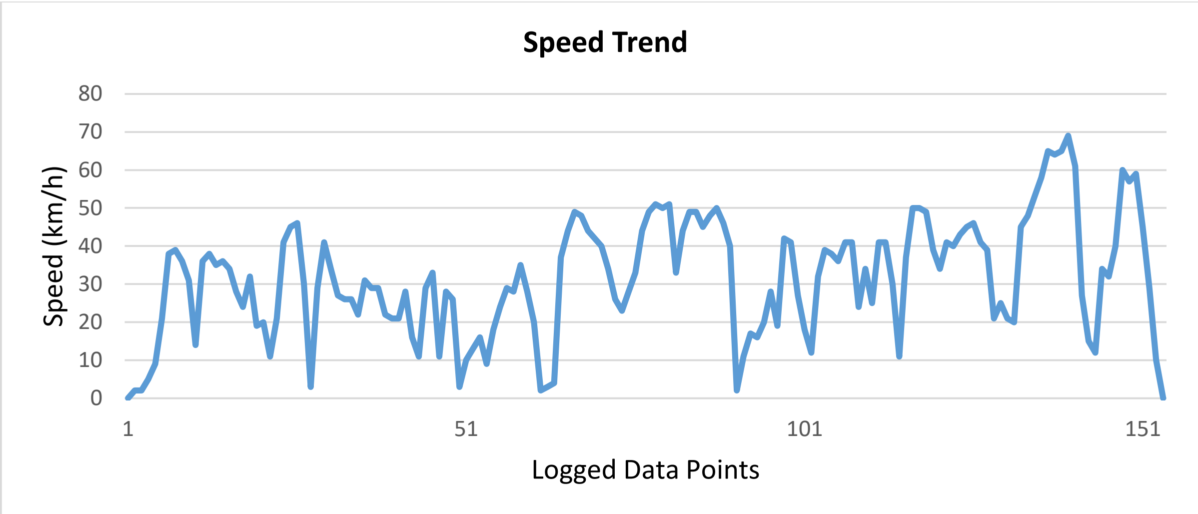


Figure 4.9. Patterns for Speed Changes

Speed patterns outlined in Figure 4.9, indicate a driving speed behaviour of below 80 km/h. This is an acceptable behaviour based on the fact that the vehicle used was from a Private Service Vehicle category limited to 110 km/h speeds. Furthermore, the road segment had no speed limits specified.

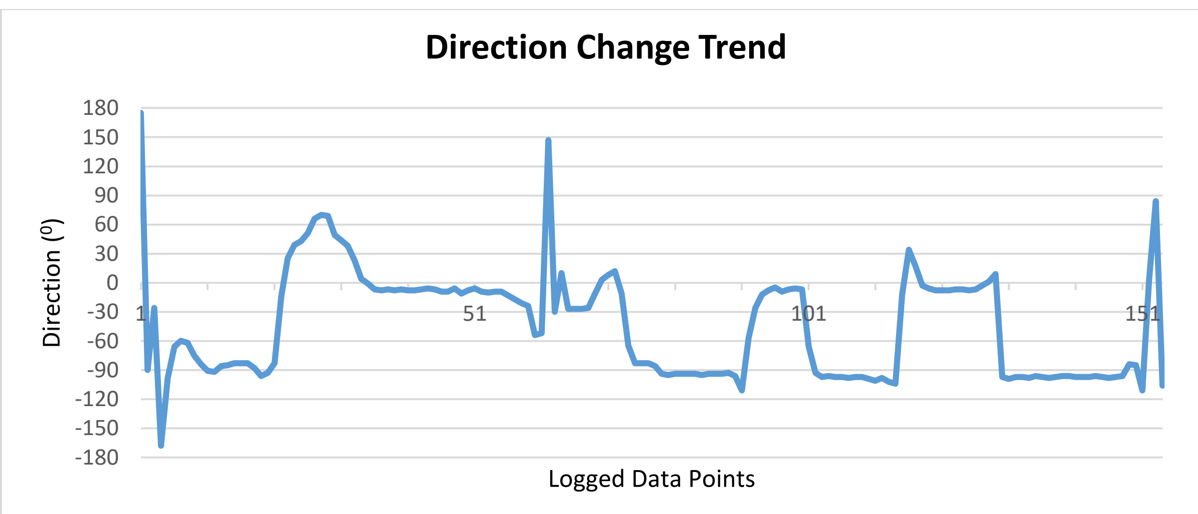


Figure 4.10. Patterns for Direction Changes

Figure 4.10 shows the direction change trends where the values on the y axis could be interpreted as follows:

- North (N): 0
- North East (NE): 1 – 89
- East (E): 90
- South East (SE): 91 – 179
- South (S): 180 and -180
- North West (NW): -1 – -89
- West (W): -90
- South West (SW): -91 – -179

Based on the results in Figure 4.10, the entire trip had numerous sharp shifts in values, a significance of many sharp corners. The results match appropriately with the route as traced on the map in Figure 4.7 in which a number of sharp corners can be seen.

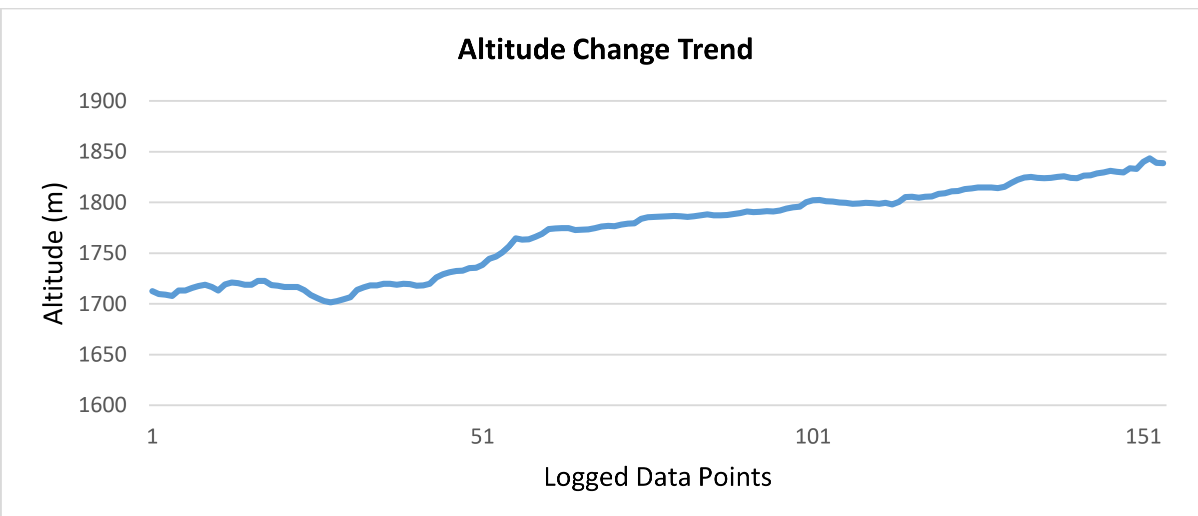


Figure 4.11. Patterns for Altitude Changes

The results in Figure 4.11 show a rise in value of altitude from the beginning of the journey to the end, but some minor down shifts around data point 26. This is an indicator of a gentle hill climb throughout the journey. The minor drop in altitude experienced a round data point 26 is an indicator of some gentle slope then back to a climb.

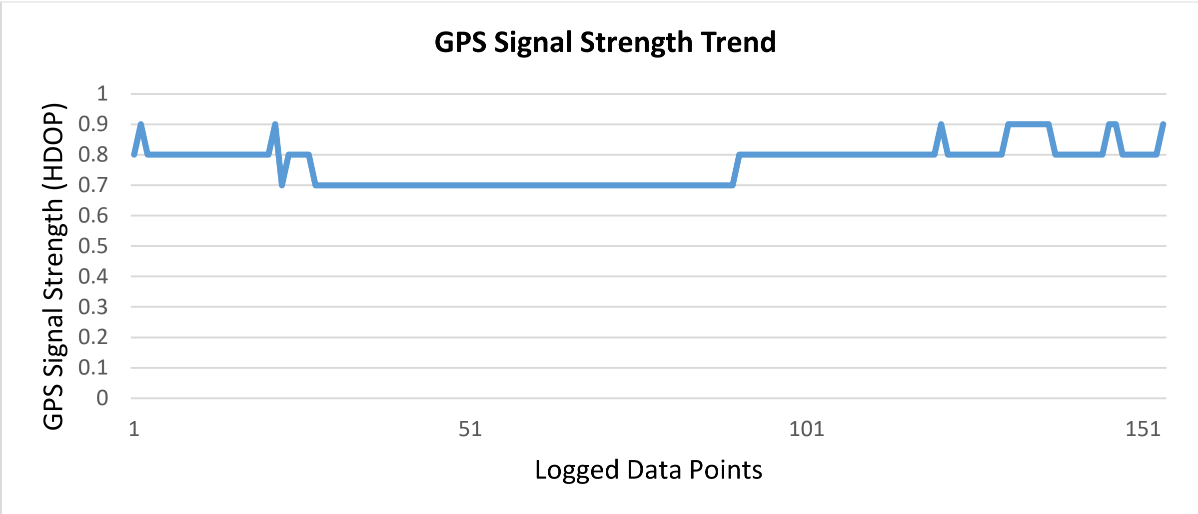


Figure 4.12. Patterns for GPS Signal Strength

The GPS signal strength pattern in Figure 4.12, signify an ideal GPS signal strength scenario since all the readings were less than 1 DOP value. This means that the GPS receiver was in a region that was in direct view of GPS satellites. It should be noted that DOP values less or equal to 1 signify ideal signal strength, 1 – 2 signify excellent signal strength, 2 – 5 signify good signal strength, 5 – 10 signify moderate signal strength, 10 – 20 signify fair signal strength while values greater than 20 signify poor signal strengths.

4.1.2.2 EXPERIMENT RESULTS

Table 4.7 shows a summary of results for the three test groups. Test Group 1 constituted of three experiments involving the same driver, same road segment on different days. To determine consistency in data collection and behaviour, Test Group 1 was subjected to six other experiments, Test Group 2 and Test Group 3. Data for the two test groups was recorded on different road segments, different days and time.

Table 4.7. Driver Behaviour Analysis

Profile Category	Behaviour Attribute	Test Group 1				Test Group 2				Test Group 3			
		Exp 1	Exp 2	Exp 3	Avg	Exp 1	Exp 2	Exp 3	Avg	Exp 4	Exp 5	Exp 6	Avg
Speeding	Lowest	0	0	0	**0.00**	0	0	0	**0**	0	0	0	**0.00**
	Highest	69	68	74	**70.33**	94	107	114	**105**	124	80	74	**95.75**
Acceleration	Normal	0.22	0.22	0.21	**0.22**	0.22	0.20	0.20	**0.21**	0.21	0.22	0.20	**0.21**
	Harsh	0.10	0.10	0.09	**0.10**	0.09	0.08	0.08	**0.08**	0.08	0.09	0.08	**0.08**
Braking	Normal	0.20	0.19	0.19	**0.19**	0.20	0.18	0.18	**0.19**	0.19	0.20	0.18	**0.19**
	Harsh	0.12	0.12	0.12	**0.12**	0.11	0.10	0.10	**0.10**	0.10	0.11	0.10	**0.10**
Cornering	Normal	0.13	0.13	0.13	**0.13**	0.13	0.12	0.12	**0.12**	0.12	0.13	0.12	**0.12**
	Harsh	0.14	0.14	0.14	**0.14**	0.14	0.12	0.12	**0.13**	0.13	0.13	0.12	**0.13**
Road Terrain	Uphill	0.28	0.29	0.27	**0.28**	0.21	0.20	0.20	**0.20**	0.22	0.22	0.21	**0.21**
	Downhill	0.17	0.16	0.17	**0.17**	0.23	0.20	0.19	**0.21**	0.20	0.21	0.19	**0.20**
Road Pattern	Straight	0.33	0.33	0.22	**0.29**	0.34	0.30	0.30	**0.31**	0.30	0.33	0.29	**0.31**
	Meander	0.12	0.13	0.12	**0.12**	0.10	0.10	0.10	**0.10**	0.12	0.11	0.11	**0.11**

4.1.2.3 DISCUSSION OF RESULTS

Two main categories of observations can be made from the results for the consistency analysis experiments:

1. Operational Environment
   - The driving environment had a terrain depicting a driver climbing i.e. rising altitudes.
   - The region had fairly straight stretches but with some corners.
2. Driver Behaviour
   - In such an environment, the driver has a high probability of driving at maximum speeds of 70.33km/h.
   - The driver has a high probability of accelerating and braking normally.
   - The cornering behaviour may be normal or harsh with a tendency of being sharp cornering.

Consistency in acceleration, braking, cornering and speeding was determined through an ANOVA single factor analysis for two random groups of three experiments each over the Test Group 1. The ANOVA single factor analysis for the same driver are as outlined in Table 4.8 to Table 4.14. The descriptive statistic in Table 0.4 and Table 0.9 under Appendix D section show normal distribution curves based on the skewness values in each case.

Table 4.8. Normal Acceleration Analysis (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.0001556	2	7.778E-05	0.875	0.464033	5.143253
Within Groups	0.0005333	6	8.889E-05			
Total	0.0006889	8				

Table 4.9. Harsh Acceleration Analysis (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.0003556	2	0.0001778	5.333333	0.046656	5.143253
Within Groups	0.0002	6	3.333E-05			
Total	0.0005556	8				

Based on the results outlined in Table 4.8 and in relation to the null hypothesis that the means for normal acceleration values for all the three test groups for the same driver are equal, since the p-value is greater than the significance level of 0.05, we accept the null hypothesis. The fact that the F value is less than the F critical value, makes it clear that there is nothing significant in the results. On the other hand, based on the results outlined in Table 4.9 and in relation to the null hypothesis that the means for harsh acceleration values for all the three test groups for the same driver are equal, since the p-value is less than the significance level of 0.05, we reject the null hypothesis. The fact that the F value is greater than the F critical value, makes it clear that there is something significant in the results. This is the reality since a human vehicle driver is expected to portray a certain consistent acceleration behaviour unless under critically uncertain conditions.

Table 4.10. Normal Braking Analysis (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	6.667E-05	2	3.333E-05	0.375	0.702332	5.143253
Within Groups	0.0005333	6	8.889E-05			
Total	0.0006	8				

Based on the results outlined in Table 4.10 and in relation to the null hypothesis that the means for normal braking values for the two test groups against the control group for the three different tests for the same driver are equal, since the p-value is greater than the significance level of 0.05, we accept the null hypothesis. The fact that the F value is less than the F critical value, makes it clear that there is nothing significant in the results. This is the reality since a human vehicle driver is expected to portray a certain consistent braking behaviour unless under uncertain conditions.

Table 4.11. Harsh Braking Analysis (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.0005556	2	0.0002778	12.5	0.007251	5.143253
Within Groups	0.0001333	6	2.222E-05			
Total	0.0006889	8				

On the other hand, the null hypothesis that the means for harsh braking behaviour values for the two test groups against the control group for the same driver are equal, is rejected since the p-value is less than the significance level of 0.05 as shown in Table 4.11. The fact that the F value is way greater than the F critical value, makes it clear that there is something significant in the results. This is the reality since a human vehicle driver is expected to portray normal braking behaviour and that harsh braking should not be a normal day to day behaviour unless under uncertain conditions.

Table 4.12. Highest Speed Analysis (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1852.6667	2	926.33333	3.236413	0.111316	5.143253
Within Groups	1717.3333	6	286.22222			
Total	3570	8				

Based on the results outlined in Table 4.12 and in relation to the null hypothesis that the means for highest speed values for the two test groups against the control group for the same driver are equal, since the p-value is greater than the significance level of 0.05, we accept the null hypothesis. The fact that the F value is less than the F critical value, makes it clear that there is nothing significant in the results. This is the reality since a human vehicle driver is expected to portray a certain consistent speeding behaviour unless under critically uncertain conditions.

Table 4.13. Normal Cornering Analysis (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	8.889E-05	2	4.444E-05	2	0.216	5.143253
Within Groups	0.0001333	6	2.222E-05			
Total	0.0002222	8				

Table 4.14. Harsh Cornering Analysis (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.0003556	2	0.0001778	3.2	0.113289	5.143253
Within Groups	0.0003333	6	5.556E-05			
Total	0.0006889	8				

Based on the results outlined in Table 4.13 and Table 4.14 and in relation to the null hypothesis that the means for normal and harsh cornering values for the two test groups against the control group for the three different tests for the same driver are equal, since the p-value in both cases are greater than the significance level of 0.05, we accept the null hypothesis. The fact that both F values are less than the F critical values, makes it clear that there is nothing significant in the results. This is the reality since a human vehicle driver is expected to portray a certain consistent cornering behaviour unless under critically uncertain conditions.

Considering the averages per category as outlined in Table 4.7, it could be concluded that the driver accelerates and brakes normally. The driver may however approach corners normally or in a harsh manner. Such a behaviour may be experienced in environments that are relatively straight with some gentle to normal terrains.

4.1.3 DATA CONSISTENCY (RESULTS WITH OBSTACLE SENSORS)

The second phase of consistency test was composed of experiments including obstacle data. This was in a move to ascertain how obstacle sensor data could complement GPS data for driver behaviour analysis. The experiments further explored whether these two sets of data can inform successful modelling of vehicle human driver behaviour through a software agent.

4.1.3.1 EXPERIMENT DESCRIPTION

A Data Collection Unit was designed using Arduino Uno Microcontroller and an ultrasonic obstacle sensor as per the circuitry in Figure 3.5. The microcontroller code is as outlined in Appendix A where the maximum obstacle distance was set to 4 meters. Initially, the experiment used an LED to signify presence or absence of an obstacle within the range.

4.1.3.2 EXPERIMENT RESULTS

The LED was continuously on for distances greater than 2 meters. This was the case regardless of whether there was an obstacle or not. This was an indicator that the obstacle sensor was continuously sensing some obstacle within its vicinity.

For distances less than 2 meters, all seemed to work fine i.e. the LED turned on whenever there was an obstacle otherwise it was off. This was however not consistent for actual road test scenarios. For instance, at certain points during actual road test, it could delay abit to turn on despite the obstacle being within the 2-meter range. For some instances, it could fail to turn on completely even with an obstacle within range. Detection seemed to work only for driving speeds below 10km/h.

4.1.3.3 DISCUSSION OF RESULTS

For the ultrasonic obstacle sensor to successfully detect an obstacle, it transmits sound waves to the object and receives reflected sound from the object. Ultrasonic sound waves must be incident on the object for it to reflect diffused incident energy. A fraction of the energy is reflected back to the sensor in form of echoes. The longer the distance the longer it takes to detect the obstacle and the weaker the reflected energy that may lead to failures in detection. The shorter the distance, the faster the detection and the lower the chances of failures in detection. Ultrasonic sensor calculate obstacle distances based on the speed of the ultrasonic wave and the time it takes for the wave to get back to the sensor.

A thorough scrutiny of test results deduced the following findings:

i) The ultrasonic obstacle sensor sends trigger signals at a very wide angle, approximately 30 degrees. Hence, for distances greater than 2 meters, the continuous obstacle sensed was the ground. A solution to this means that the sensor has to be raised too high for the detection angle not to visualise the ground within it range.
ii) For an object to be detected, ultrasonic sound waves must be incident on the object for it to reflect diffused incident energy, in cases of objects in motion, establishment of incidence may fail to occur. Furthermore, reflected waves may fail to reach back to the sensor due to changing distances. This may have contributed to the obstacle detection inconsistencies for distances less than 2 meters during the test drive.
iii) The type and nature of surface that the ultrasonic sound wave hits has an effect on the formulation of incidence and the strength of the reflected wave. In actual road test, the types of objects detected varied widely i.e. some had wide surfaces, smooth surfaces, among others. This may have also contributed to the obstacle detection inconsistencies.

In actual driving scenario, using a GPS receiver alone for data collection has a great potential in determining the behaviour of the driver with probabilities relating to the operational environment. The data gained from the sample test could act as training sets for an intelligent agent aimed at modelling a driver's behaviour. The ultrasonic obstacle sensor operating at less than 2 meters' detection distance and for speeds less than or equals to 10km/h will be too limiting for driver behaviour analysis unless if used to only detect extremely risky behaviour relating to driving at very close ranges to other vehicles. Such close range driving distances are the norm in city scenarios especially during traffic jams. This may go against the norm for profiling drivers based on risky behaviour as the results may not be a true reflection of the driver's behaviour.

4.1.4 PRESTUDY CHALLENGES AND THEIR EFFECTS TO THE MAIN STUDY

The success of the prestudy faced a number of unforeseen challenges, including but not limited to:

1. The ultrasonic proximity sensor used was limited to detection distances less than 2 meters to the obstacle as opposed to the earlier anticipated 10 meters' range. The closer the sensor gets to the obstacle, the better the accuracy of detection. The sensor type was heavily affected by motion and interference from other environmental factors like wind. This created a major challenge that led to many false positive detections. Unfortunately, these limitations were tough to mitigate as they were beyond control in this study. The main study hence considered obstacles detected at distances less than or equals to 2 meters.

2. Weather conditions on the other hand had an effect on proximity sensor's functionality i.e. the sensor was affected by the presence of humidity on the sensing surface. Hence, could only function under low humidity levels to no humidity in the atmosphere. Proximity sensor data was hence used in cases where the data was collected during times when humidity levels were appropriate for the proximity sensor.

3. Drivers driving Public Service Vehicles for ferrying passengers tend to change for almost all trips in a day. Most of the time, they drive to certain point of the journey then hand over to other drivers. This posed a major challenge in monitoring a particular driver for a good enough period for better pattern identification. The main study hence assumed that the behaviour of a given set of Public Service Vehicle drivers could serve as a representation of other drivers. However, the study had to introduce a categorization of Public Service Vehicle drivers based on the operational environment i.e. town service driver or long distance driver. This helped to avoid a generalization of behaviour over a large set of drivers operating under varied environments.

4. It was extremely hard to use proximity sensors without drivers realizing that they were being monitored. This was because, proximity sensors have to be physically fitted on the vehicle hence visible to drivers. Hence, only one sample vehicle was instrumented to serve the purpose of testing the model's capability to detect obstacles and incorporate the data in driver behaviour analysis during the main study.

4.1.5 CONCLUSION OF PRESTUDY RESULTS

The prestudy yielded stable, consistent and reliable results. These results helped in the validation of data collection instruments and data analysis algorithms. Prestudy outcome led to the publication of a research paper on the shortcomings of ultrasonic sensor technology for vehicle driver assistance and profiling [81]. The paper basically outlines the fact that though the technology is powerful for obstacle detection, it faces some challenges in certain applications especially due to the wide beam width.

4.2 MAIN STUDY'S GENERAL AND DEMOGRAPHIC INFORMATION

The study samples were categorized based on different road categories and service vehicle categories.

4.2.1 CATEGORIES OF ROADS IN KENYA

Kenyan roads have been adapted to a large range of structures and types in order to achieve a common goal of transportation under varied conditions. The specific purpose, mode of transport, and location of a road determine the characteristics it must have to maximize its usefulness.

Roads can be classified as generally private roads, lower capacity highways, higher capacity highways, limited access grade-separated highways or multi modal. Lower capacity highways are often single carriageways while higher capacity highways are often dual carriageways. Kenya just like other countries in the world has different types and categories of roads spread throughout the nation. This study focused on dual carriageways, single carriageways and highways to represent the various categories of roads.

4.2.2 VEHICLE SERVICE CATEGORIES IN KENYA

All vehicles plying on Kenyan roads are categorized as either Private or Public Service Vehicles (PSV). Private Service Vehicles are basically individually owned or attached to private companies or organisations. Private Service Vehicles are the majority on Kenyan roads. On the other hand, Public Service Vehicles are either Government owned or vehicles that are privately owned but dedicated to serve the general public. A special category of Public Service Vehicles well known in Kenya are "matatus". Matatu is a Swahili name that refers to a category of vehicles that serves to transport people from one location to another. Matatus are basically passenger vehicle service group of vehicles.

4.2.3 SAMPLED DRIVERS

This study sampled drivers who operate on three categories of roads, namely, dual carriageways, single carriageways and highways. The choice of roads also represented both urban and rural settings. Furthermore, the sampled drivers also represented both service vehicle categories i.e. Private Service Vehicles and Public Service Vehicles. Figure 4.13 depict the percentage of drivers sampled per vehicle service category where 15 drivers were selected per vehicle service category.

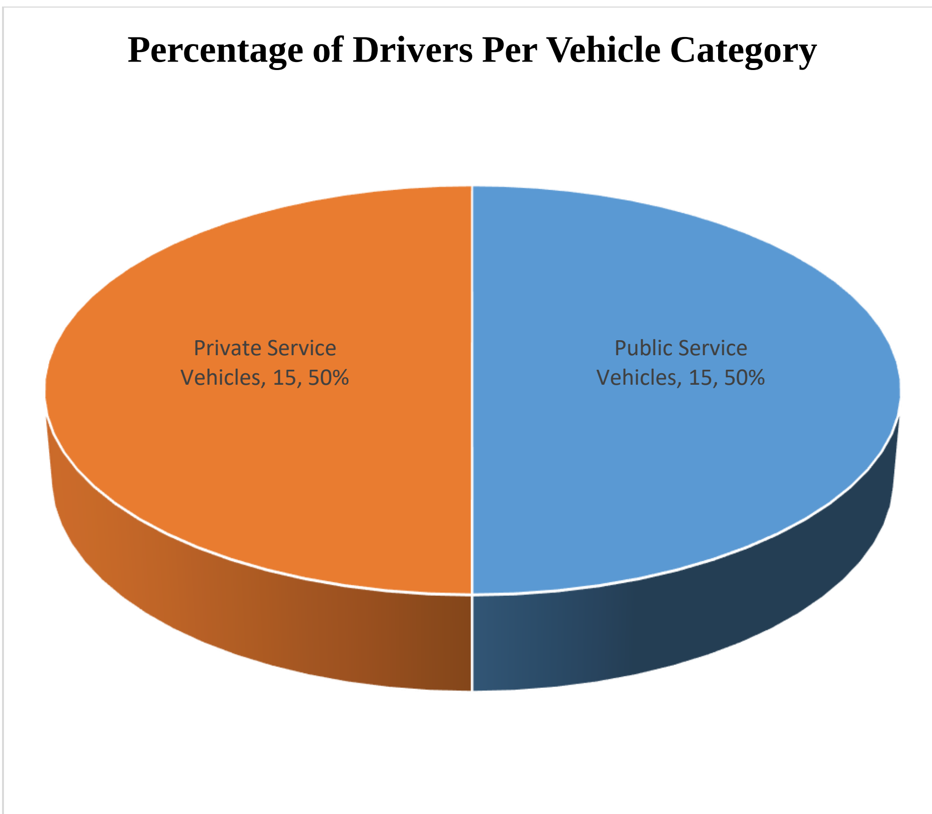


Figure 4.13. Sampled Drivers per Service Vehicle Category

To represent the three road categories, the 30 drivers were chosen from three categories such that each category had a total of 10 drivers as shown in Figure 4.14. The 10 drivers per road category were equally distributed to represent the two vehicle service categories.

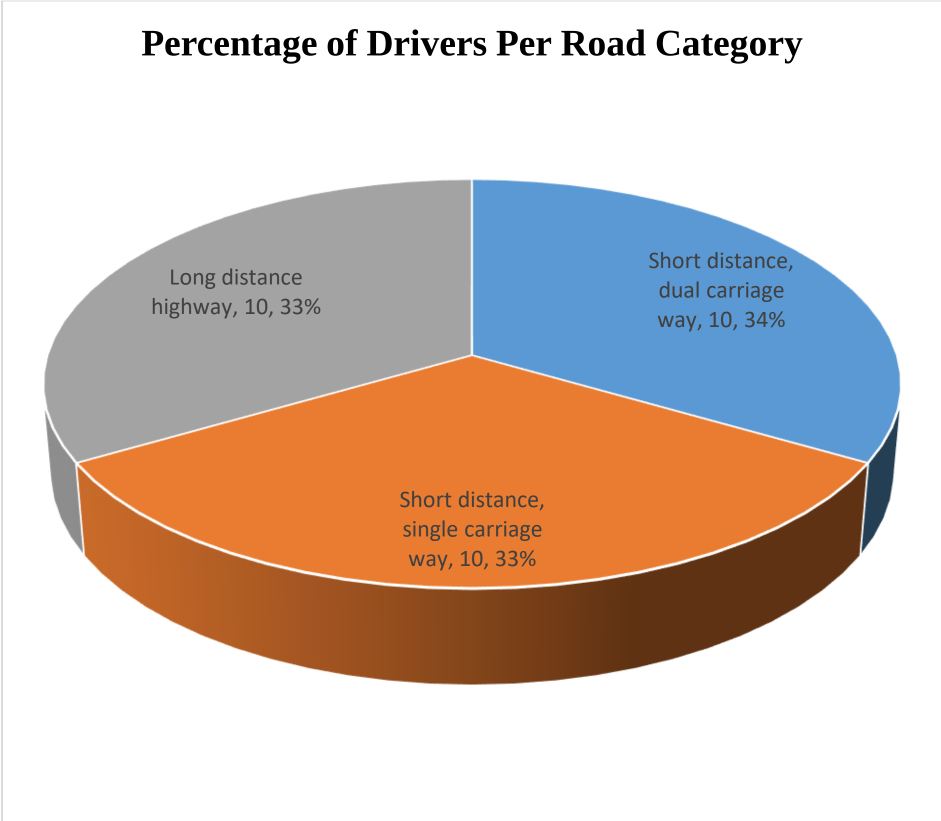


Figure 4.14. Sampled Drivers per Road Category

4.2.4 SAMPLED DRIVERS' EXPERIENCE

According to the Kenyan Traffic Act, all vehicle drivers are required to possess a driving license. This serves as a permit to drive a vehicle on Kenyan roads. Acquiring this vital document is a predefined process guided by the Kenyan traffic laws. Driving licenses fall into different categories, and are issued based on an individuals need upon successful training and passing of a standard driving test. The driving test is facilitated by the Traffic Department of the Kenya Police.

All the sampled drivers were licensed to drive vehicles on Kenyan roads with valid driving licenses. Ascertaining experience level of a vehicle driver is deemed to be a complex process since many parameters are required. To try and take care of this, the sampled drivers were expected to portray evidence of active driving for at most one year from the point of selection.

4.3 MAIN STUDY RESULTS AND DISCUSSION BASED ON OBJECTIVES

The overall motivation of the study was to contribute towards the efforts of understanding driver behaviour and possibly aid in future strategies for minimising if not fully controlling the rate of fatalities and road carnages worldwide. This was demonstrated through thorough monitoring and analysis of human vehicle driver behaviour in comparison with a driver agent operating under dynamic conditions. Two sets of performance measures were used to evaluate the behaviour of human vehicle drivers and the driver agent. The first set was composed of five behavioural analyses, that is, speeding behaviour, acceleration behaviour, deceleration behaviour, stopping behaviour and cornering behaviour. The other set was the detection of the operational environment, limited to road terrain and road pattern.

4.3.1 ESTABLISHMENT OF VEHICLE DRIVER BEHAVIOUR

Considering objective one and research question one, the study established that vehicle drivers are agents that operate under partially observable; dynamic; nondeterministic; continuous; sequential; multiagent; and unknown environments. Such environments are the most complex to model. The study further established that a vehicle driver's driving style depends on a number of factors that include familiarity of the operational environment, type of road, road pattern, terrain of the road, time of day, presence or absence of obstacles. Hence, driving styles may be characterized based on different factors that include overtaking, speeding, acceleration, braking, lane changing trends among other trends. The sunburst in Figure 4.15 summarises some of these factors, where every slice represents a set of factors that could comprise a vehicle driver's environment.

Figure 4.15. A Sunburst Enumeration of Factors Characterizing a Vehicle Driver's Environment

The categorizations are paired as follows:

i) Familiarity of the environment: familiar or unfamiliar.
ii) Type of road: single or dual carriageway
iii) Road pattern: meandering or straight
iv) Terrain of the road: hilly or flat
v) Time of day: day or night
vi) Obstacles: obstacle or no obstacle

Other layers of factors that could be considered in the driver's operational environment include mechanical condition of vehicles, vehicle model, weather condition, driving region, state of the driver, and state of other road users among others.

4.3.1.1 DRIVER BEHAVIOUR PARAMETERS

To effectively determine the behaviour of vehicle drivers operating under diverse environments, Table 4.15 presents parameters required per behavioural category while Table 0.1 under Appendix B outlines behavioural probabilities that serve as metric thresholds for some behaviour. The threshold column in Table 4.15 indicates the limits set out by authorising bodies outlined in the authorisation column.

Table 4.15. Driver Behaviour Categorisation with their Respective Data Parameters

Category	Behaviour	Threshold	Authorisation	Parameters
Speeding	Normality in Speeding	**Non Built-up Areas** Single Carriageway: ▪ Private cars: <=100km/h ▪ Commercial: <=80km/h ▪ Vehicles with Trailers: <=65km/h Dual Carriageway: ▪ Private cars: <=110km/h ▪ Commercial: <=80km/h ▪ Vehicles with Trailers: <=65km/h **Built-up Area** ▪ Recommended speed for all vehicle categories is 50km/h or less in some instances Any values above the recommended speeds per region were considered to be overspeeding instances	▪ Standard metric set out by National Transport and Safety Authority (NTSA) in Kenya	▪ Speed ▪ Timestamp ▪ Latitude ▪ Longitude ▪ Altitude

Category	Behaviour	Threshold	Authorisation	Parameters
Acceleration and Deceleration	Normality in Acceleration and Deceleration	Speed increment against time difference: ▪ There are variable thresholds based on different factors: ○ Vehicle type ○ Vehicle strength ▪ Accelerations ranging from 0 to 5 meters per square seconds were considered to be normal acceleration with any values above 5 meters per square seconds being considered to be harsh acceleration instances. ▪ Decelerations ranging from 0 to -5 meters per square seconds were considered to be normal braking with any values below -5 meters per square seconds being considered to be harsh braking instances.	▪ Vehicle manufacturers specifications ▪ No standard metric	▪ Speed ▪ Timestamp ▪ Latitude ▪ Longitude ▪ Altitude
Cornering	Normality in Cornering	▪ Left or right angle change against speed levels were considered as a measure. ▪ A turn of less than 45 degrees was considered to be a normal corner while 45 and above degrees turn qualified to be a sharp corner. ▪ Normal or harsh cornering depends on speeds against the degree changes in addition to altitude changes. This was based on probabilities as outlined in Table 0.1.	▪ Vehicle manufacturers specifications ▪ No standard metric	▪ Speed ▪ Timestamp ▪ Latitude ▪ Longitude ▪ Altitude ▪ Direction (angle) ▪ Turn angle ▪ Obstacle data

Category	Behaviour	Threshold	Authorisation	Parameters
Stopping	Normality in Braking to an actual Stop	Speed decrement against time difference: Stopping Sight Distance (SSD) [78] was considered: SSD = (Perception-reaction Distance) + (Braking Distance) SSD = 0.278 Vt + (0.039 V^2)/a (Metric) Where: V = design or initial speed in kilometers per hour (km/h) a = deceleration rate in meter per square seconds (m/s^2) t = brake reaction time, in seconds (s)	▪ World standard metric on Stopping Sight Distance	▪ Speed ▪ Timestamp ▪ Latitude ▪ Longitude ▪ Altitude ▪ Obstacle data

A number of data analysis techniques exist. However, accuracy in the determination of driving styles for behavioural analysis is dependent on data analysis methodologies and techniques used. The study established that due to the stochastic, dynamic and partially observable nature of drivers' operational environment, appropriate data analysis techniques must involve elements of probabilistic reasoning. The study hence settled on Bayesian Networks as the most suitable methods. This was due to the following factors:

1. Bayesian Networks are probabilistic graphical models hence, represented by a graph accompanied by a table of probabilities:
    a) The graphical part of the Bayesian Network indicates the dependence or independence between variables hence providing an easy to comprehend visual knowledge representation tool [82].
    b) The use of probabilities accommodates uncertainty in quantifying the dependencies between variables [82].
2. Bayesian Networks are a type of statistical model that maps a set of variables and their conditional dependencies.
3. Bayesian classification theories are useful analyses forms for prediction of future data trends and intelligent decision-making [80].

It must however be noted that the behaviour of a vehicle driver varies greatly based on different factors against time. Hence, successful analysis of driver behaviour should be kind of a time series analysis. The study hence considers the power of Dynamic Bayesian Network (DBN) that enables them to relate adjacent time steps. DBNs are therefore referred to as 2-Time-slice Bayesian Network (2TBN). According to the 2TBN, at any given time t, the value of a variable can be calculated from the internal regressors and immediate prior value at time t-1. This was useful in the determination of driver behaviour per given time-slice with the average of several time-slice behaviour constituting a full driver behaviour profile.

To determine actual driver behaviour, the study consider three categories of roads, namely, dual carriageway, single carriage way and highways. A set of 15 drivers from the Private Service Vehicle category and 15 drivers from the Public Service Vehicle category. The two broad Service Vehicle categories accommodate light, heavy and commercial vehicle subcategories. The sample of 30 drivers were all labelled D1 to D15 per Service Vehicle category. They were then equally distributed in each of the three road categories, such that each category had 10 drivers, 5 from each Service Vehicle category as follows:

i) Dual carriageway: drivers D1, D2, D3, D4 and D5 from both Service Vehicle categories.
ii) Single carriageway: drivers D6, D7, D8, D9 and D10 from both Service Vehicle categories.
iii) Highways: drivers D11, D12, D13, D14 and D15 from both Service Vehicle categories.

4.3.1.2 SPEEDING, ACCELERATION AND DECELERATION BEHAVIOUR: DUAL CARRIAGEWAYS

Private Service Vehicle Drivers

The first set of five Private Service Vehicle drivers, labeled D1, D2, D3, D4 and D5, was subjected to the Southern Bypass, a tarmac dual carriageway that connects Mombasa road to the Waiyaki way. The road segment is as highlighted in Figure 4.16, ranging from Langata road intersection all the way to the Waiyaki way intersection. The road segment was composed of relatively straight stretches with few clear corners. The road terrain was relatively flat with gentle slops at some point. The road had few gentle, speed breaker kind of bumps with no potholes. Other factors included daytime, dry weather, a very short stretch of a built-up area, Kikuyu, close to the Waiyaki way intersection.

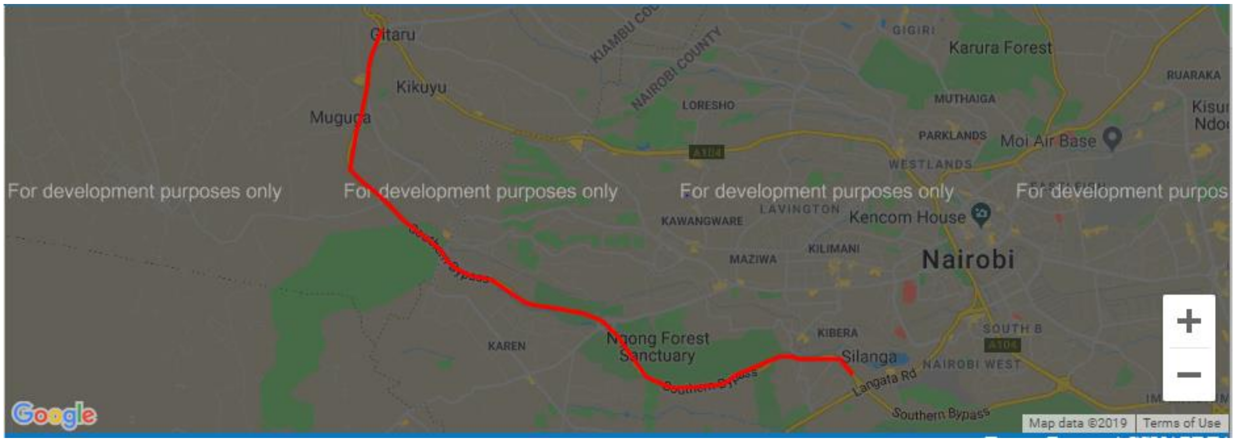


Figure 4.16. Southern Bypass (Dual Carriageway)

The study established that Private Service Vehicle drivers tend to drive at relatively high speeds on dual carriageways. This is as shown in Table 4.16 where average speeds were ranging from lows of 74 km/h to highs of 99 km/h. The maximum speed ever recorded was 126 km/h. Only one out of the five sampled drivers recorded the highest speed that was within the required speed limit of 100 km/h without considering any speed limited zones.

Table 4.16. Speeding Behaviour for Private Service Drivers (Descriptive Statistics)

	D1	*D2*	*D3*	*D4*	*D5*
Mean	89.79167	73.79167	98.95833	88.64583	90.60417
Standard Error	3.454229	2.772548	1.782987	1.945965	2.569899
Median	95.5	77	100	94	98
Mode	115	91	109	98	103
Standard Deviation	23.9316	19.20877	12.35289	13.48204	17.80478
Sample Variance	572.7216	368.977	152.594	181.7655	317.0102
Kurtosis	-1.56065	-1.23649	-0.12686	0.984906	0.930629
Skewness	-0.28926	-0.51333	-0.42931	-1.1307	-1.23422
Range	68	59	54	59	75
Minimum	48	39	72	46	36
Maximum	116	98	126	105	111
Sum	4310	3542	4750	4255	4349
Count	48	48	48	48	48
Confidence Level(95.0%)	6.949013	5.577646	3.586906	3.914778	5.169969

Table 4.17. Speeding Behaviour for Private Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	15922.97	4	3980.744	12.49395	3.13E-09	2.410058
Within Groups	74874.21	235	318.6137			
Total	90797.18	239				

The p-value that is significantly greater than 0.05 and F value significantly greater than F critical are indicators that there is a significant difference in driving speed behaviour for any given set of Private Service Vehicle drivers operating on dual carriageways. This is as depicted in Table 4.17. This is however a complete inverse of the acceleration behaviour for the same set of drivers using the same dataset as outlined in Table 4.18, where, the average acceleration and deceleration falls between -0.025 and 0.171 meters per square seconds. Furthermore, the p-value that is greater than 0.05 and F value that is less than the F critical is an indicator that there is nothing significant in acceleration and deceleration behaviour for any given set of Private Service Vehicle drivers operating on dual carriageways. This is as depicted in Table 4.19.

Table 4.18. Acceleration and Deceleration Behaviour for Private Service Drivers (Descriptive Statistics)

	D1	*D2*	*D3*	*D4*	*D5*
Mean	0.059375	0.032292	0.012917	0.171458	-0.02521
Standard Error	0.06908	0.022869	0.052037	0.056644	0.06681
Median	0.16	0.045	0.095	0.14	0
Mode	0.28	0	0.14	0.14	0
Standard Deviation	0.478599	0.15844	0.360525	0.392445	0.462873
Sample Variance	0.229057	0.025103	0.129979	0.154013	0.214251
Kurtosis	11.35035	-0.00562	1.011115	2.693319	3.200285
Skewness	-2.78648	-0.32779	-1.01967	-0.52997	-1.31864
Range	2.98	0.73	1.61	2.22	2.6
Minimum	-2.22	-0.37	-1.15	-1.2	-1.67
Maximum	0.76	0.36	0.46	1.02	0.93
Sum	2.85	1.55	0.62	8.23	-1.21
Count	48	48	48	48	48
Confidence Level(95.0%)	0.138971	0.046006	0.104686	0.113954	0.134404

Table 4.19. Acceleration and Deceleration Behaviour for Private Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.064877	4	0.266219	1.769127	0.135804	2.410058
Within Groups	35.36292	235	0.15048			
Total	36.42779	239				

Considering speeding, acceleration and deceleration trend analysis for Private Service Vehicle drivers, it is emerging that the drivers tend to drive at significantly different high speeds on dual carriageways but their acceleration and deceleration trends tend to converge. Both speeding and acceleration analyses had platykurtic kind of distribution recorded for all the drivers based on the kurtosis and skewness values except acceleration analyses for driver D1 and D5 that experienced kurtosis values higher than 3 with slight skewness to the left.

Public Service Vehicle Drivers

The first set of five Public Service Vehicle drivers, labeled D1, D2, D3, D4 and D5, was subjected to the Waiyaki Way, a tarmac dual carriage way ranging from Nairobi City to Limuru Town as highlighted in Figure 4.17. The road segment was composed of relatively straight stretches with few clear corners. The road terrain was relatively flat with gentle slops at some point. The road had no bumps and no potholes. Other factors included daytime, dry weather, composed of both built-up and nonbuilt-up sections.

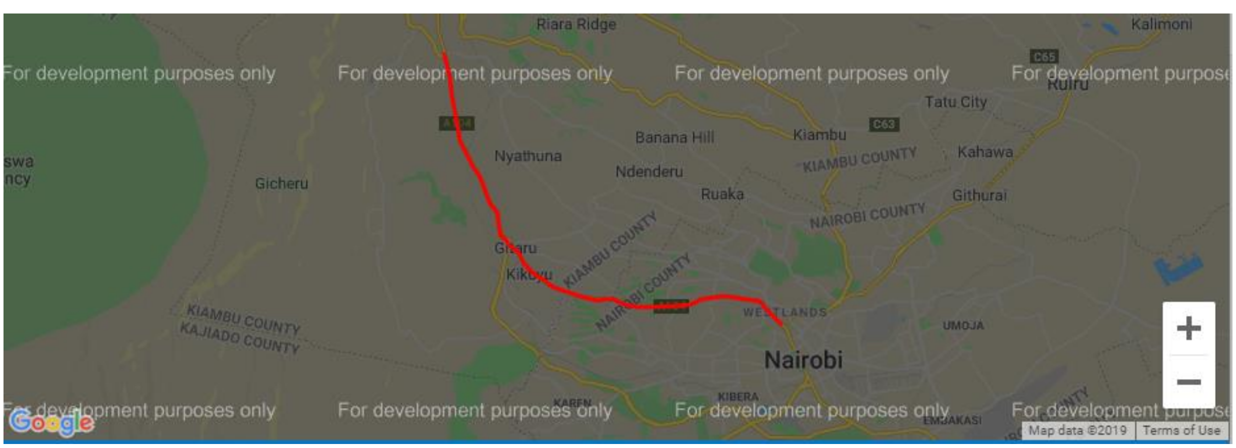


Figure 4.17. Waiyaki Way (Dual Carriageway)

The study established that Public Service Vehicle drivers tend to drive at relatively low speeds compared to Private Service Vehicle drivers on dual carriageways. The behaviour is however limited to passenger Public Service Vehicle drivers. This is as shown in Table 4.20, where, average speeds were ranging from lows of 53 km/h to highs of 72 km/h. The highest speed ever recorded was 91 km/h. Surprisingly, all the five sampled drivers recorded maximum speeds that were above the recommended speed limit of 80 km/h for Public Service Vehicles' category in Kenya.

Table 4.20. Speeding Behaviour for Public Service Drivers (Descriptive Statistics)

	D1	*D2*	*D3*	*D4*	*D5*
Mean	59.33649	63.27014	53.42654	56.06635	72.27488
Standard Error	1.256328	0.975572	1.272379	1.20801	0.684946
Median	64	65	58	59	74
Mode	66	66	59	59	79
Standard Deviation	18.24922	14.171	18.48237	17.54736	9.949409
Sample Variance	333.0339	200.8172	341.5981	307.9099	98.99075
Kurtosis	0.782874	1.325255	0.771157	0.83857	1.255119
Skewness	-1.21871	-0.92837	-1.1392	-1.06734	-0.95664
Range	78	85	79	80	58
Minimum	5	6	2	3	31
Maximum	83	91	81	83	89
Sum	12520	13350	11273	11830	15250
Count	211	211	211	211	211
Confidence Level(95.0%)	2.47663	1.923169	2.508272	2.38138	1.35025

Table 4.21. Speeding Behaviour for Public Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	45716.03	4	11429.01	44.56276	1.37E-34	2.380406
Within Groups	269293.5	1050	256.47			
Total	315009.5	1054				

Just like for the case of Private Service Vehicle drivers, speed analysis for the sampled set of Public Service Vehicle drivers recorded a p-value greater than 0.05 and F value significantly greater than F critical. This is an indicator that there is a significant difference in driving speed behaviour for any given set of passenger Public Service Vehicle drivers operating on dual carriageways. This is however a complete inverse of their acceleration behaviour. Table 4.22 shows an analysis of the acceleration patterns for the same set of drivers, where, the average acceleration and deceleration falls between -0.002 and 0.023 meters per square seconds. Furthermore, the p-value that is greater than 0.05 and F value that is less than the F critical is an indicator that there is nothing significant in acceleration and deceleration behaviour for any given set of passenger Public Service Vehicle drivers on dual carriageways. This is as depicted in Table 4.23.

Table 4.22. Acceleration and Deceleration for Public Service Drivers (Descriptive Statistics)

	D1	*D2*	*D3*	*D4*	*D5*
Mean	0.006872	-0.00232	0.023318	0.003649	0.02218
Standard Error	0.02273	0.020877	0.019804	0.025724	0.023106
Median	0.02	0	0.07	0.03	0
Mode	0	-0.07	-0.07	0	0
Standard Deviation	0.330167	0.303255	0.287666	0.373662	0.335627
Sample Variance	0.10901	0.091964	0.082752	0.139623	0.112646
Kurtosis	2.557307	2.220148	1.848208	1.568919	13.3957
Skewness	-0.92035	-0.48875	-0.52264	-0.71833	-1.44524
Range	2.09	2.22	1.94	2.5	3.65
Minimum	-1.32	-1.18	-0.94	-1.53	-2.43
Maximum	0.77	1.04	1	0.97	1.22
Sum	1.45	-0.49	4.92	0.77	4.68
Count	211	211	211	211	211
Confidence Level(95.0%)	0.044807	0.041155	0.03904	0.05071	0.045549

Table 4.23. Acceleration and Deceleration Behaviour for Public Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.110761	4	0.02769	0.258307	0.904643	2.380406
Within Groups	112.5589	1050	0.107199			
Total	112.6696	1054				

Considering speeding trend and acceleration and deceleration trend analysis for Public Service Vehicle drivers, it emerges that the drivers tend to drive at significantly different speeds but their acceleration and deceleration trends tend to converge. Both speeding and acceleration analyses had platykurtic kind of distribution recorded for all the drivers based on the kurtosis and skewness values except acceleration analyses for driver D5 that experienced kurtosis values higher than 3 with slight skewness to the left.

4.3.1.3 SPEEDING, ACCELERATION AND DECELERATION BEHAVIOUR: SINGLE CARRIAGEWAYS

Private Service Vehicle Drivers

The second set of five Private Service Vehicle drivers, labeled D6, D7, D8, D9 and D10, was subjected to the Magadi road, a tarmac single carriageway that connects Ongata Rongai Town and the Bomas of Kenya. The road segment also branches at the Masai Lodge junction to Africa Nazarene University, Main Campus gate. The road segment is as highlighted in Figure 4.18. The road segment was composed of relatively straight stretches with few clear corners on the northern end. The southern segment had some sharp unclear corners. The road terrain was relatively flat with gentle slops at some point with no potholes. One point of the segment had a short steep hill climb. Other factors included daytime, dry weather, composed of both built-up and nonbuilt-up sections.

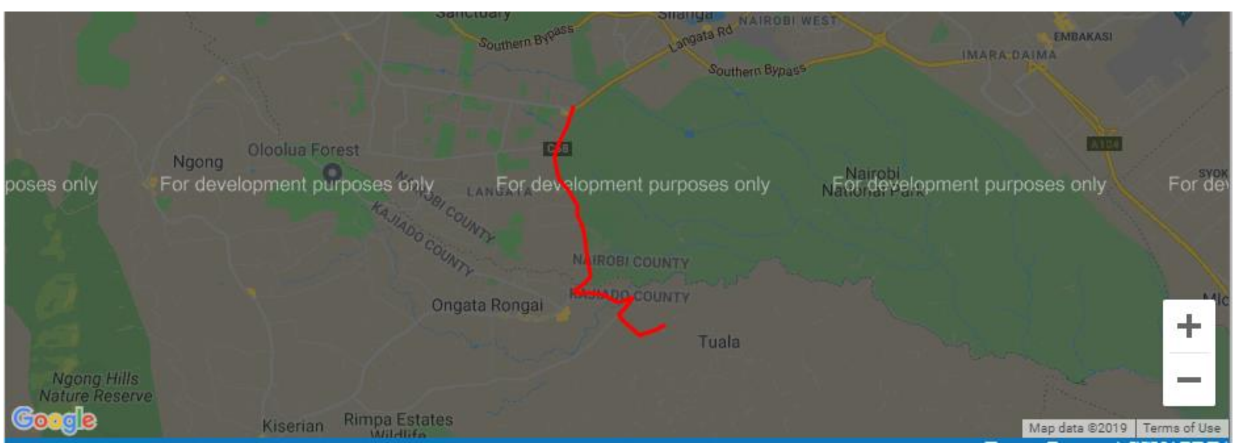


Figure 4.18. Magadi Road and Masai Lodge Road (Single Carriageway)

The study established that Private Service Vehicle drivers tend to drive at relatively low speeds on single carriageways compared to dual carriageways. This is as shown in Table 4.24, where, average speeds were ranging from lows of 32 km/h to highs of 38 km/h. The highest speed ever recorded was 72 km/h. Hence, all the sampled drivers were operating within the required speed limit of 100 km/h without considering any speed limited zones.

Table 4.24. Speeding Behaviour for Private Service Drivers (Descriptive Statistics)

	D6	*D7*	*D8*	*D9*	*D10*
Mean	31.72826	32.98913	32.91304	37.6087	35.08696
Standard Error	1.454198	1.450118	1.660411	1.56458	1.720541
Median	33.5	35	30.5	37.5	34
Mode	31	18	25	30	45
Standard Deviation	13.94818	13.90904	15.9261	15.00693	16.50285
Sample Variance	194.5517	193.4614	253.6407	225.2078	272.344
Kurtosis	-0.88554	-1.05655	-0.33991	-0.47977	-1.00674
Skewness	-0.26857	-0.30264	0.534842	0.152712	0.02795
Range	54	51	65	63	62
Minimum	3	5	7	8	5
Maximum	57	56	72	71	67
Sum	2919	3035	3028	3460	3228
Count	92	92	92	92	92
Confidence Level(95.0%)	2.888586	2.880481	3.298202	3.107846	3.417643

Table 4.25. Speeding Behaviour for Private Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1982.326	4	495.5815	2.175119	0.070835	2.391539
Within Groups	103667.7	455	227.8411			
Total	105650	459				

The p-value that is slightly greater than 0.05 and F value slightly less than F critical are indicators that there is nothing significant in driving speed behaviour for any given set of Private Service Vehicle drivers operating on single carriageways. This is as represented in Table 4.25. The case is similar to the acceleration and deceleration behaviour for the same set of drivers using the same dataset as outlined in Table 4.26, where, the average acceleration and deceleration falls between 0.022 and 0.094 meters per square seconds. Furthermore, the p-value that is greater than 0.05 and F value that is less than the F critical are indicators that there is nothing significant in acceleration and deceleration behaviour for any given set of Private Service Vehicle drivers operating on a single carriageway. This is as shown in Table 4.27.

Table 4.26. Acceleration and Deceleration Behaviour for Private Service Drivers (Descriptive Statistics)

	D6	*D7*	*D8*	*D9*	*D10*
Mean	0.041739	0.033152	0.094891	0.024239	0.022391
Standard Error	0.04819	0.039132	0.041861	0.043712	0.040778
Median	0.06	0.055	0.11	0.06	0.065
Mode	0	0	0	0.28	0.28
Standard Deviation	0.46222	0.375344	0.401512	0.419273	0.391125
Sample Variance	0.213647	0.140883	0.161212	0.17579	0.152979
Kurtosis	1.706445	1.20754	5.315453	0.695908	1.634751
Skewness	-0.49252	0.122686	-1.0756	-0.3724	-0.72573
Range	2.75	2.07	2.85	2.33	2.33
Minimum	-1.5	-0.87	-1.83	-1.22	-1.46
Maximum	1.25	1.2	1.02	1.11	0.87
Sum	3.84	3.05	8.73	2.23	2.06
Count	92	92	92	92	92
Confidence Level(95.0%)	0.095723	0.077732	0.083151	0.086829	0.081

Table 4.27. Acceleration and Deceleration Behaviour for Private Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.328216	4	0.082054	0.485808	0.746178	2.391539
Within Groups	76.85053	455	0.168902			
Total	77.17874	459				

Considering speeding, acceleration and deceleration trend analysis, it is emerging that Private Service Vehicle drivers tend to drive at relatively slower speeds on single carriageways compared to dual carriageways. However, there is nothing significantly different in their driving speed, acceleration and deceleration trends. Both speeding and acceleration analyses had platykurtic kind of distribution recorded for all the drivers based on the kurtosis and skewness values.

Public Service Vehicle Drivers

The second set of five Private Service Vehicle drivers, labeled D6, D7, D8, D9 and D10, was subjected to a tarmac single carriageway segment of the Nairobi – Nakuru Highway as highlighted in Figure 4.19. The segment ranged from Kijabe to Gilgil. The road segment was composed of relatively straight stretches with few clear corners. The road terrain was relatively flat but with some regions with long sloping stretches. Several speed bumps existed in the segment with no potholes. Other factors included daytime, dry weather, composed of both built-up and nonbuilt-up sections.

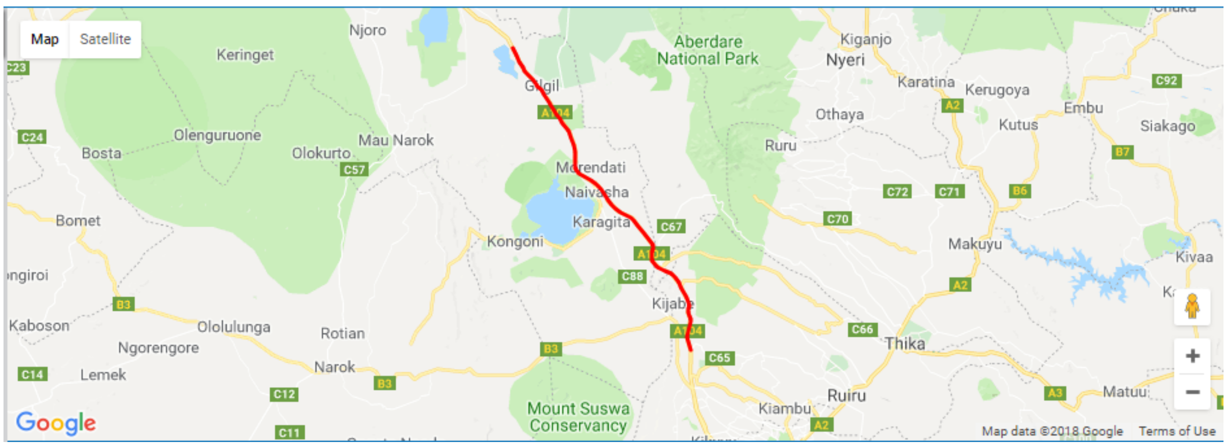


Figure 4.19. Kijabe to Gilgil (Single Carriageway)

The study established that Public Service Vehicle drivers tend to drive at relatively high speeds compared to Private Service Vehicle drivers while plying on single carriageways. This behaviour is however limited to passenger Public Service Vehicle drivers. This is as shown in Table 4.28, where, average speeds ranged from lows of 52 km/h to highs of 66 km/h. The highest speed ever recorded was 94 km/h. Surprisingly, all the five sampled drivers recorded highest speeds that were above the recommended speed limit of 80 km/h for Public Service Vehicles in Kenya. This was a similar case for dual carriageways.

Table 4.28. Speeding Behaviour for Public Service Drivers (Descriptive Statistics)

	D6	*D7*	*D8*	*D9*	*D10*
Mean	64.68306	65.78962	53.28962	52.37432	60.78415
Standard Error	0.924783	0.987446	1.077689	1.250746	1.11426
Median	69	69	57	57	67
Mode	72	84	0	79	78
Standard Deviation	17.69213	18.89095	20.61741	23.92819	21.31704
Sample Variance	313.0116	356.8679	425.0775	572.5581	454.4163
Kurtosis	2.529827	-0.4418	0.788044	-1.17459	-0.05975
Skewness	-1.60974	-0.68537	-1.07583	-0.34912	-0.84441
Range	89	75	88	89	89
Minimum	0	19	0	0	0
Maximum	89	94	88	89	89
Sum	23674	24079	19504	19169	22247
Count	366	366	366	366	366
Confidence Level(95.0%)	1.818571	1.941797	2.119259	2.459573	2.191174

Table 4.29. Speeding Behaviour for Public Service Vehicle Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	57589.94	4	14397.48	33.92542	2.42E-27	2.376804
Within Groups	774505	1825	424.3863			
Total	832094.9	1829				

Just like for the case of Private Service Vehicle drivers, speed analysis for the sampled set of Public Service Vehicle drivers recorded a p-value significantly greater than 0.05 and F value significantly greater than F critical as depicted in Table 4.29. This is an indicator that there is a significant difference in driving speed behaviour for any given set of passenger Public Service Vehicle drivers. This is however a complete inverse of the acceleration behaviour. Table 4.30 shows an analysis of the acceleration patterns for the same set of drivers where average acceleration and deceleration falls between 0.0003 and 0.0104 meters per square seconds. Furthermore, the p-value that is greater than 0.05 and F value that is less than the F critical are indicators that there is nothing significant in acceleration and deceleration behaviour for any given set of passenger Public Service Vehicle drivers operating on single carriageways. This is as shown in Table 4.31.

Table 4.30. Acceleration and Deceleration Behaviour for Public Service Drivers (Descriptive Statistics)

	D6	*D7*	*D8*	*D9*	*D10*
Mean	0.010027	0.000301	0.007377	0.010137	0.010464
Standard Error	0.019159	0.01758	0.016444	0.018691	0.018021
Median	0	0	0	0.04	0
Mode	0	0	0	0	0
Standard Deviation	0.366541	0.336333	0.314591	0.357573	0.344771
Sample Variance	0.134352	0.11312	0.098967	0.127858	0.118867
Kurtosis	6.34314	1.698256	4.178697	2.850152	3.034325
Skewness	-0.9057	-0.25385	-0.68156	-1.13701	-0.27228
Range	3.65	2.29	2.92	2.49	2.56
Minimum	-2.43	-1.11	-1.74	-1.72	-1.39
Maximum	1.22	1.18	1.18	0.77	1.17
Sum	3.67	0.11	2.7	3.71	3.83
Count	366	366	366	366	366
Confidence Level(95.0%)	0.037677	0.034572	0.032337	0.036755	0.035439

Table 4.31. Acceleration and Deceleration Behaviour for Public Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.027027	4	0.006757	0.056955	0.993979	2.376804
Within Groups	216.505	1825	0.118633			
Total	216.532	1829				

Considering speeding trend and acceleration and deceleration trend analysis it emerges that Public Service Vehicle drivers operating on single carriageways tend to drive at significantly different speeds but their acceleration and deceleration trends tend to converge. The case is similar to the same category of drivers operating on dual carriageways. Both speeding and acceleration analyses had platykurtic kind of distribution recorded for all the drivers based on the kurtosis and skewness values except acceleration analyses for driver D6, D8 and D10 that experienced kurtosis values higher than 3.

4.3.1.4 SPEEDING, ACCELERATION AND DECELERATION BEHAVIOUR: LONG DISTANCE HIGHWAYS

Private Service Vehicle Drivers

The last set of five Private Service Vehicle drivers, labeled D11, D12, D13, D14 and D15, was subjected to the Nairobi – Nakuru Highway. This was a 150 km tarmac highway that connects Nairobi City and Nakuru Town. The highway was composed of both single carriageway and dual carriageway segments with the longest stretch being single carriageway. The road segment analysed is as highlighted in Figure 4.20. The road terrain was a mixed mode i.e. composed of a mix of flat, sloping and hill climbing, clear and unclear corners. Several speed bumps existed at different segment of the road with no potholes. Other factors included daytime, dry weather, composed of both built-up and nonbuilt-up sections.

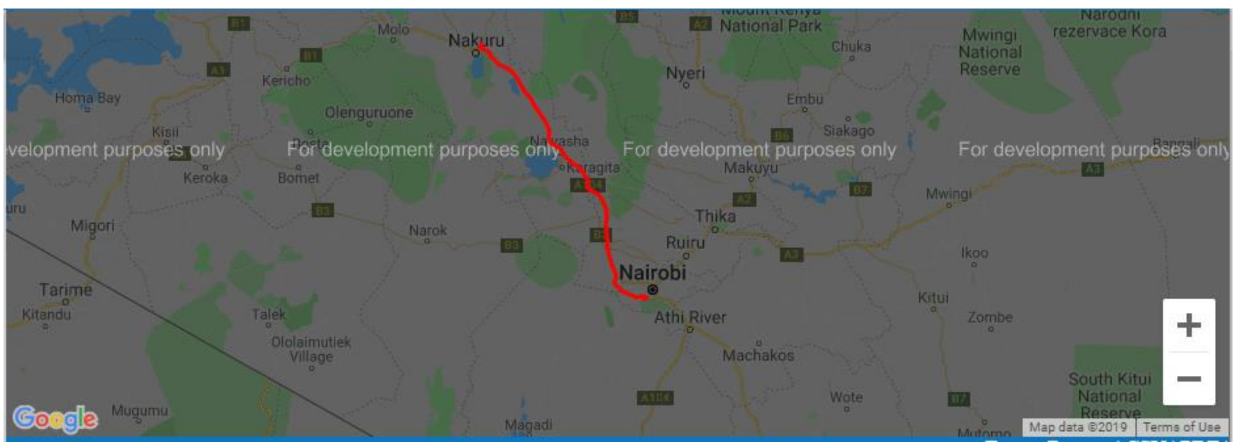


Figure 4.20. Nairobi – Nakuru Highway (Long Distance Highway)

The segment had relatively straight stretches with both clear and unclear corners spread throughout. The road terrain was relatively flat but with some regions with long sloping stretches. Several speed bumps existed in the segment. Other factors included daytime, dry weather, composed of both built-up and nonbuilt-up sections.

The study established that Private Service Vehicle drivers tend to drive at relatively high speeds on long distance highways. This is as shown in Table 4.32, where, average speeds were ranging from lows of 44 km/h to highs of 63 km/h. The maximum speed ever recorded was 114 km/h with only two out of the five sampled drivers recording highest speeds that were within the required speed limit of 100 km/h without considering any speed limited zones.

Table 4.32. Speeding Behaviour for Private Service Drivers (Descriptive Statistics)

	D11	*D12*	*D13*	*D14*	*D15*
Mean	54.36921	43.9133	55.63378	63.00448	53.03438
Standard Error	0.859628	0.975585	0.859026	0.734885	0.996342
Median	55	48	56	65	52
Mode	54	0	43	64	52
Standard Deviation	22.23432	25.23355	22.21874	19.00784	25.77041
Sample Variance	494.365	636.732	493.6726	361.2979	664.1141
Kurtosis	-0.51406	-1.14656	-0.33493	0.468476	-0.5296
Skewness	-0.2703	-0.20293	-0.05196	-0.65665	0.079605
Range	98	89	105	103	114
Minimum	2	0	0	0	0
Maximum	100	89	105	103	114
Sum	36373	29378	37219	42150	35480
Count	669	669	669	669	669
Confidence Level(95.0%)	1.687899	1.915583	1.686717	1.442963	1.956338

Table 4.33. Speeding Behaviour for Private Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	124808.5	4	31202.12	58.86789	4.32E-48	2.374593
Within Groups	1770321	3340	530.0363			
Total	1895130	3344				

The p-value that is significantly greater than 0.05 and F value greater than F critical are indicators that there is a significant difference in driving speed behaviour for any given set of Private Service Vehicle drivers operating on long distance highways. This is as depicted in

Table 4.33. It is however a complete inverse of the acceleration behaviour for the same set of drivers using the same dataset as outlined in Table 4.34, where, the average acceleration and deceleration falls between -0.006 and 0.025 meters per square seconds. Furthermore, the p-value that is greater than 0.05 and F value that is less than the F critical are indicators that there is nothing significant in acceleration and deceleration behaviour for any given set of Private Service Vehicle drivers. This is as depicted in Table 4.35.

Table 4.34. Acceleration and Deceleration Behaviour for Private Service Vehicle Drivers (Descriptive Statistics)

	D11	*D12*	*D13*	*D14*	*D15*
Mean	0.010972	0.020314	0.025336	-0.00607	0.020613
Standard Error	0.012836	0.011292	0.010748	0.014024	0.012703
Median	0.01	0.01	0.02	0	0.03
Mode	0	0	0	0	0
Standard Deviation	0.331994	0.292069	0.278006	0.362744	0.328576
Sample Variance	0.11022	0.085304	0.077287	0.131583	0.107962
Kurtosis	3.115314	4.010804	5.788723	3.467327	4.178339
Skewness	-0.95855	-0.98032	-1.21933	-0.841	-1.10151
Range	2.63	2.44	2.55	3.03	3.12
Minimum	-1.57	-1.46	-1.55	-1.83	-2.15
Maximum	1.06	0.98	1	1.2	0.97
Sum	7.34	13.59	16.95	-4.06	13.79
Count	669	669	669	669	669
Confidence Level(95.0%)	0.025203	0.022172	0.021105	0.027537	0.024944

Table 4.35. Acceleration and Deceleration Behaviour for Private Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.417297	4	0.104324	1.018081	0.396474	2.374593
Within Groups	342.2544	3340	0.102471			
Total	342.6717	3344				

Considering speeding, acceleration and deceleration trend analysis for Private Service Vehicle drivers, it is emerging that the drivers tend to drive at significantly different speeds on long distance highways but their acceleration and deceleration trends tend to converge. Speeding analyses had platykurtic kind of distribution recorded for all the drivers based on the kurtosis and skewness values. However, acceleration analyses had leptokurtic kind of distributions based on kurtosis values that were higher than 3.

Public Service Vehicle Drivers

The last set of five Public Service Vehicle drivers, labeled D11, D12, D13, D14 and D15, was subjected to the Nairobi – Nakuru Highway. This is a 150 km tarmac highway that connects Nairobi City and Nakuru Town. The highway is composed of both single carriageway and dual carriageway segments with the longest stretch being single carriageway. The road segment analysed is as highlighted in Figure 4.21. The road terrain was a mixed mode i.e. composed of a mix of flat, sloping and hill climbing, clear and unclear corners. Several speed bumps existed at different segment of the road with no potholes. Other factors included daytime, dry weather, composed of both built-up and nonbuilt-up sections.

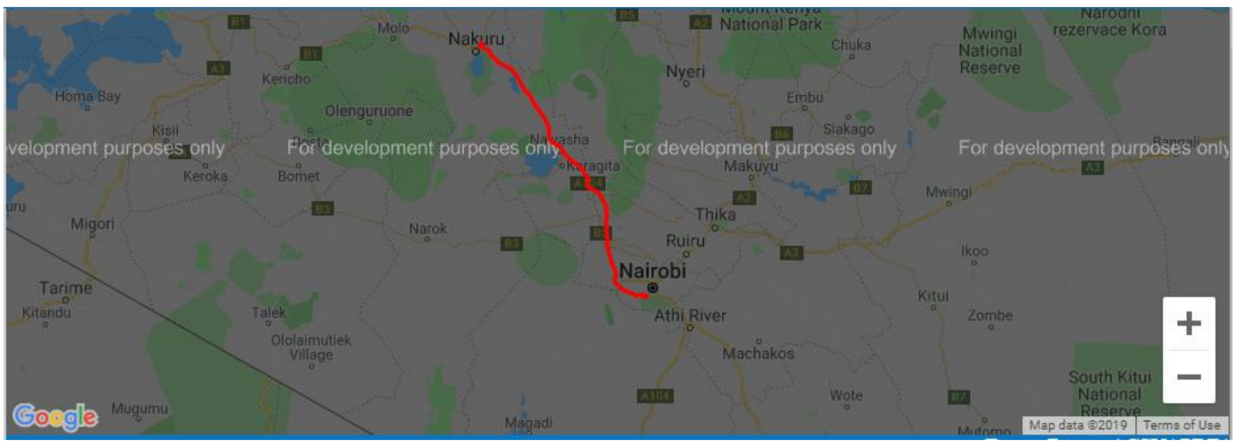


Figure 4.21. Nairobi – Nakuru Highway (Long Distance Highway)

The study established that Public Service Vehicle drivers tend to drive at relatively similar speeds on single carriageways and long distance highways. This behaviour is however limited to passenger Public Service Vehicle drivers. This is as shown in Table 4.36, where, average speeds range from lows of 55 km/h to highs of 61 km/h. The maximum recorded speed was 98 km/h. Surprisingly, all the five sampled drivers recorded maximum speeds that were above the recommended speed limit of 80 km/h for Public Service Vehicles in Kenya.

Table 4.36. Speeding Behaviour for Public Service Drivers (Descriptive Statistics)

	D11	*D12*	*D13*	*D14*	*D15*
Mean	60.57399	55.85351	55.87743	59.06726	54.68909
Standard Error	0.673278	0.805548	0.565572	0.653119	0.731345
Median	64	60	56	63	58
Mode	59	71	56	66	76
Standard Deviation	17.41436	20.83553	14.62853	16.89293	18.91627
Sample Variance	303.2599	434.1192	213.9939	285.3712	357.8253
Kurtosis	0.875746	-0.13347	-0.55237	2.097956	-0.3144
Skewness	-0.94484	-0.64485	-0.20869	-1.36495	-0.62235
Range	92	98	71	91	87
Minimum	3	0	16	0	0
Maximum	95	98	87	91	87
Sum	40524	37366	37382	39516	36587
Count	669	669	669	669	669
Confidence Level(95.0%)	1.321996	1.581711	1.110512	1.282412	1.436012

Table 4.37. Speeding Behaviour for Public Service Drivers (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	16548.81	4	4137.203	12.97279	1.75E-10	2.374593
Within Groups	1065172	3340	318.9139			
Total	1081721	3344				

Just like for the case of Private Service Vehicle drivers, speed analysis for the sampled set of Public Service Vehicle drivers recorded a p-value significantly greater than 0.05 and F value significantly greater than F critical as depicted in Table 4.37. This is an indicator that there is a significant difference in driving speed behaviour for any given set of passenger Public Service Vehicle drivers operating on long distance highways. This is however a complete inverse of the acceleration behaviour. Table 4.38 shows an analysis of the acceleration patterns for the same set of drivers, where, average acceleration and deceleration falls between -0.0001 and 0.007 meters per square seconds. Furthermore, the p-value that is greater than 0.05 and F value that is less than the F critical as shown in Table 4.39 are indicators that there is nothing significant in acceleration and deceleration behaviour for any given set of Public Service Vehicle drivers on long distance highways.

Table 4.38. Acceleration and Deceleration for Public Service Drivers (Descriptive Statistics)

	D11	*D12*	*D13*	*D14*	*D15*
Mean	0.00417	0.002631	0.001674	-0.0001	0.007115
Standard Error	0.012644	0.014314	0.012523	0.011818	0.012924
Median	0	0	0	0	0
Mode	0	0	0	0	0
Standard Deviation	0.327048	0.370231	0.323906	0.305661	0.334278
Sample Variance	0.106961	0.137071	0.104915	0.093429	0.111742
Kurtosis	1.469336	2.381775	1.390875	3.440716	2.00527
Skewness	-0.35	-0.53078	0.276539	-0.80736	-0.62083
Range	2.59	2.85	2.3	2.71	2.39
Minimum	-1.53	-1.46	-1.11	-1.67	-1.32
Maximum	1.06	1.39	1.19	1.04	1.07
Sum	2.79	1.76	1.12	-0.07	4.76
Count	669	669	669	669	669
Confidence Level(95.0%)	0.024828	0.028106	0.024589	0.023204	0.025376

Table 4.39. Acceleration and Deceleration Behaviour for Public Service Driver (ANOVA Single Factor)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.019929	4	0.004982	0.044957	0.99619	2.374593
Within Groups	370.1502	3340	0.110823			
Total	370.1701	3344				

Considering speeding trend and acceleration and deceleration trend analysis for Public Service Vehicle drivers, it emerges that the drivers tend to drive at significantly different speeds but their acceleration and deceleration trends tend to converge.

4.3.1.5 SUMMARY FOR SPEEDING, ACCELERATION AND DECELERATION BEHAVIOUR

Table 4.40 outlines a summary of driver behaviour with respect to speeding, acceleration and deceleration. This is analysed with respect to the three categories of roads, namely, dual carriageways, single carriageways and highways and two vehicle service categories, namely, Public Service and Private Service.

Table 4.40. Speeding, Acceleration and Deceleration Behaviour Summary

	Dual Carriageway		**Single Carriageway**		**Highway**	
	Public Service	**Private Service**	**Public Service**	**Private Service**	**Public Service**	**Private Service**
Average Speed	53 – 75 km/h	74 – 99 km/h	52 – 66 km/h	32 – 38 km/h	55 – 61 km/h	44 – 63 km/h
Highest Speed	91 km/h	126 km/h	94 km/h	72 km/h	98 km/h	114 km/h
Average Acceleration / Deceleration	-0.002 – 0.023 m/s^2	-0.025 – 0.171 m/s^2	0.0003 – 0.0104 m/s^2	0.022 – 0.094 m/s^2	-0.0001 – 0.007 m/s^2	-0.006 – 0.025 m/s^2
Highest Acceleration Margin	1.22 m/s^2	1.02 m/s^2	1.22 m/s^2	1.25 m/s^2	1.39 m/s^2	1.20 m/s^2
Highest Deceleration Margin	-2.43 m/s^2	-2.22 m/s^2	-2.43 m/s^2	-1.87 m/s^2	-1.67 m/s^2	-2.15 m/s^2

Conclusively, using road worthy vehicles on well-maintained, relatively flat dual carriageways road category with gentle slops at some points, Private Service Vehicle drivers presented high average driving speeds, acceleration and deceleration in comparison to Public Vehicle Service drivers. This is based on the fact that Private Service Vehicle drivers average speed ranged between 74 and 99 km/h with the highest speed being 126 km/h and average acceleration and deceleration ranging between -0.025 and 0.171 m/s^2 while Public Service Vehicle drivers recorded average speeds between 53 and 75 km/h with the highest speed being 91 km/h and average acceleration and deceleration ranging between -0.002 and 0.023 m/s^2. Public Service Vehicle drivers presented high acceleration and deceleration margins compared to Private Service Vehicle drivers. This is evident by the fact that the highest acceleration margin recorded for Private Service Vehicles drivers was 1.02 m/s^2 compared to that of Public Service Vehicle drivers that stood at 1.22 m/s^2. Similarly, the highest deceleration margin recorded for Private Service Vehicles drivers was -2.22 m/s^2 compared to that of Public Service Vehicle drivers that stood at -2.43 m/s^2. Based on the analysis, datasets for driver D1, D3 and D4 under the Public Service Vehicle category were considered for training the agent. Datasets for driver D2 and D4 of the Private Service Vehicle category were also considered in the training set for the driver agent. The choices were based on the fact that all the drivers' maximum acceleration and deceleration margins were within acceptable ranges. A compromise was however made for instances here highest speeds did not exceed 5 km/h above the recommended speeds.

On well-maintained single carriageways road category with a mix of flat, sloping and hill climbing, clear and unclear corners, Public Service Vehicle drivers presented high average driving speeds with low average acceleration and deceleration in comparison to Private Vehicle

Service drivers. This is based on the fact that Public Service Vehicle drivers average speed ranged between 52 and 66 km/h with the highest speed being 94 km/h and average acceleration and deceleration ranging between 0.0003 and 0.0104 m/s^2 while Private Service Vehicle drivers recorded average speeds between 32 and 38 km/h with the highest speed being 72 km/h and average acceleration and deceleration ranging between 0.022 and 0.094 m/s^2. Private Service Vehicle drivers presented high acceleration margins compared to passenger Public Service Vehicle drivers. This is evident by the fact that the highest acceleration margin recorded for Private Service Vehicles drivers was 1.25 m/s^2 compared to that of Public Service Vehicle drivers that stood at 1.22 m/s^2. On the contrary, Public Service Vehicle drivers presented high deceleration margins compared to passenger Private Service Vehicle drivers. This is evident by the fact that the highest deceleration margin recorded for Private Service Vehicles drivers was -1.87 m/s^2 compared to that of Public Service Vehicle drivers that stood at -2.43 m/s^2. Based on the analysis, datasets for all the sampled drivers under the Private Service Vehicle category were included in the training set for the driver agent while none of the Public Service Vehicle drivers was considered for inclusion in the training dataset. This was based on the fact that all Private Service Vehicle drivers exhibited highest speeds within the required limits while all the Public Service Vehicle drivers recorded highest speeds that were way above the allowable speed limits for the service vehicle category.

On well-maintained long distance highways road category with a mix of flat, sloping and hill climbing, clear and unclear corners, some stretches with bumps, Both Public Service Vehicle and Private Service drivers presented overlapping average driving speeds. However, Private Service Vehicle drivers presented high average acceleration and deceleration in comparison to Public Vehicle Service drivers. This is based on the fact that Public Service Vehicle drivers average speed ranged between 55 and 61 km/h with the highest speed being 98 km/h and average acceleration and deceleration ranging between -0.0001 and 0.007 m/s^2 while Private Service Vehicle drivers recorded average speeds between 44 and 63 km/h with the highest speed being 114 km/h and average acceleration and deceleration ranging between -0.006 and 0.025 m/s^2. Public Service Vehicle drivers presented high acceleration margins compared to Private Service Vehicle drivers. This is evident by the fact that the highest acceleration margin recorded for Private Service Vehicles drivers was 1.20 m/s^2 compared to that of Public Service Vehicle drivers that stood at 1.39 m/s^2. On the contrary, Private Service Vehicle drivers presented high deceleration margins compared to passenger Public Service Vehicle drivers. This is evident by the fact that the highest deceleration margin recorded for Private Service Vehicles drivers was -2.15 m/s^2 compared to that of Public Service Vehicle drivers that stood at -1.67 m/s^2. Based on the analysis, datasets for drivers D11, D12, D13 and D14 of the Private Service Vehicle category were included in the training set for the driver agent while none of the Public Service Vehicle drivers was considered for inclusion. This was based on the fact that four out of the five Private Service Vehicle drivers exhibited highest speeds within the required limits while all the Public Service Vehicle drivers recorded highest speeds that were way above the allowable speed limits for the service vehicle category.

In summary, Private Service Vehicle drivers record high speeds on dual carriageways and highways compared to single carriageways. Furthermore, they record high average speed ranges on dual carriageways. On the other hand, Public Service Vehicle drivers record high acceleration margins on dual carriageways and highways and high deceleration margins on dual carriageways and single carriageways. On a general scale, Private Service Vehicle drivers present high average acceleration / deceleration margins.

4.3.1.6 STOPPING BEHAVIOUR

Stopping behaviour was computed as a comparison of the actual distance taken to stop and the distance established based on the standard Stopping Sight Distance metric as outlined in Table 4.15. Table 4.41 show a sample analysis for three drivers D1, D3 and D5 of the public service vehicle category. Data for driver D2 and D4 did not have instances of stopping. The divers were operating on a Dual carriageway. Considering the fact that Kenyan dual carriageway have a 100 km/h design speed, the Stopping Sight Distance based on this design speed is meant to be 184.21 meters. The study however based the Stopping Sight Distance on initial speeds as opposed to design speed since a driver starts applying brakes when driving at varied speeds. Perception-reaction time of 2.5 seconds and deceleration rate of 3.4 m/s^2 were used in the determination of Stopping Sight Distance. Under all circumstances, the Stopping Sight Distance based on initial speed and the actual distance to stop were all below the Stopping Sight Distance based on design speed since at no point did any driver brake from speeds of 100 km/h to 0 km/h.

Table 4.41. Stopping Behaviour Analysis

Driver D1					
Data Point	**Speed (km/h)**	**Change in Time (s)**	**Deceleration Rate (m/s^2)**	**SSD Based on Initial Speed (m)**	**Actual Distance to Stop (m)**
278	10	9	-1.2		
279	0	12	-0.23	8.10	33.36
Driver D3					
Data Point	**Speed (km/h)**	**Change in Time (s)**	**Deceleration Rate (m/s^2)**	**SSD Based on Initial Speed (m)**	**Actual Distance to Stop (m)**
38	1	4	-0.35		
39	0	17	-0.02	0.75	4.76
54	43	4	-0.28		
55	0	12	-1	51.09	143.28
58	8	9	0.25		
59	0	51	-0.04	6.29	113.22
64	6	10	0.08		
65	0	10	-0.17	4.58	16.7
71	19	79	0.02		
72	0	16	-0.33	17.35	84.48
83	16	10	0.22		
84	0	10	-0.44	14.06	44.4
94	4	14	-0.52		
95	0	6	-0.19	2.96	6.66
111	4	5	-0.61		
112	0	10	-0.11	2.96	11.1
127	15	9	0.37		
128	0	11	-0.38	13.01	45.87
133	2	6	-0.19		
134	0	10	-0.06	1.46	5.6
136	4	10	0.03		
137	0	10	-0.11	2.96	11.1
140	4	10	0.06		
141	0	10	-0.11	2.96	11.1
147	3	6	0.05		
148	0	10	-0.08	2.19	8.3
155	5	10	-0.03		
156	0	10	-0.14	3.76	13.9
159	1	11	-0.15		
160	0	10	-0.03	0.71	2.8
166	8	5	-0.06		

Data Point	Speed (km/h)	Change in Time (s)	Deceleration Rate (m/s^2)	SSD Based on Initial Speed (m)	Actual Distance to Stop (m)
167	0	10	-0.22	6.29	22.2
168	2	10	0.06		
169	0	10	-0.06	1.41	5.6
174	5	5	0.06		
175	0	5	-0.28	3.76	6.95
197	2	20	-0.03		
198	0	10	-0.06	1.41	5.6
472	9	4	-0.56		
473	0	11	-0.23	7.18	27.5
493	10	7	0.4		
494	0	13	-0.21	8.10	36.14
Driver D5					
Data Point	**Speed (km/h)**	**Change in Time (s)**	**Deceleration Rate (m/s^2)**	**SSD Based on Initial Speed (m)**	**Actual Distance to Stop (m)**
67	39	4	-2.43		
68	0	13	-0.83	44.55	140.79
71	6	9	0.19		
72	0	11	-0.15	4.58	18.37
75	3	10	0.08		
76	0	10	-0.08	2.19	8.3
279	15	5	-0.89		
280	0	10	-0.42	13.01	41.7

It is evident that for all the three drivers' stopping instances, the actual distance taken to stop was greater than the standard Stopping Sight Distances computed based on initial speed. This was an indicator that the driver's braking to stopping behaviour was within acceptable standard margins. A similar computation was done for all the 30 sampled drivers under the two categories i.e. Public Service Vehicle category and Private Service Vehicle category. All the sampled drivers presented stopping behaviour that was within acceptable margins, hence, qualifying the data collected from them to be used for training the driver agent.

4.3.1.7 CORNERING BEHAVIOUR

The study established that there are no standard metrics for the determination of cornering behaviour. The behaviour was hence determined using the margin of direction change in comparison to time taken and speed. This behaviour was not monitored for human vehicle drivers. It was however incorporated in the driver agent with a special algorithm used to determine what could be termed as acceptable or unacceptable behaviour.

4.3.2 FORMULATION OF DRIVER BEHAVIOUR DATASET

Considering successful prestudy and main study results, in view of objective two and research questions two, an effective dataset on driver behaviour patterns constitutes of the following raw GPS data variables:

1. Coordinates (latitude and longitude)
2. Altitude
3. Speed
4. Direction
5. GPS time
6. GPS signal strength

These data variables lead to another key set of computed variables that are also critical for the driver behaviour dataset. Majority of these computed variables are essential for use in the Bayesian Network. These are:

1. Change in direction
2. Change in altitude
3. Change in time
4. Acceleration and deceleration
5. Stopping Sight Distance (SSD)
6. Distance to stop

A complete dataset on driver behaviour should also incorporate data on presence or absence of obstacles in the operational environment of the driver. The study however excluded proximity sensor data for the data set due to challenges and limitations outlined in the previous section. However, a robotic vehicle agent could incorporate the proximity sensor if simulated on shorter distances computed in centimeters.

A route map for the region constituting the dataset enhances the dataset by indicating a visual perspective of the driving environment. To enhance the dataset further, a recorded video of real diving environment and scenarios was also considered in some cases. This helps build confidence in potential future users of the dataset.

A full dataset for both the prestudy and main study is available in a separate MS-Excel file. However, Appendix E presents sample datasets for driver D1 and D4 of the Public Service Vehicle and D2 and D4 of the Private Service Vehicle categories. The two drivers are part of the fourteen drivers that were selected for training, validation and testing of the driver agent. The full dataset for all the drivers that formulated the driver behaviour dataset will later be availed online as an open access dataset for usage by interested parties.

4.3.3 DEVELOPMENT AND EVALUATION OF A VEHICLE DRIVER AGENT

The dataset formulated under objective two acted as a foundation for the development of the vehicle driver agent in reference to objective three and four, with a focus on research question three and four. An intelligent agent that models a human vehicle driver operating under challenging diverse environments was hence developed. To better visualize the agent's actions under diverse environments, the study focused on a software agent.

The agent underwent three main phases: training, validation and testing. During the training phase, the agent was subjected to the chosen dataset collected from human vehicle drivers to facilitate learning. After successful training, the software agent underwent validation as an unbiased evaluation of fitness while tuning the model's hyper parameters. Finally, it was then put in a real environment for the testing phase.

The study addressed a contingency kind of problem since exact prediction is impossible and its solution requires a strategy, a contingency plan that specifies what action to take based on the received percepts. This was achieved through utility functions to provide agent's internal performance measures in two main perspectives. Firstly, the function offers appropriate tradeoffs amongst conflicting goals. Secondly, it weighs success likelihood against the importance of goals. If the internal utility function and the external performance measures are in agreement, then it chooses actions to maximize utility.

4.3.3.1 DESIGN OF THE DRIVER AGENT

A web based software agent was designed that operated in parallel with a human vehicle driver without activating mechanical actuators. It instead operates as a software agent with screen display of actions to be undertaken. The agent provided dashboard indicators for various actions that include speeding, acceleration, deceleration, braking and turning. To achieve these actions, the agent's percepts were limited to GPS data and proximity sensor data gathered by various sensors during actual vehicle operational period.

Figure 4.22 shows a sample dashboard for the software agent. The dashboard contains human vehicle driver behaviour in form of probabilities where acceleration, braking and cornering trends are each expressed in two perspectives, namely, normal and harsh. The perspective with the highest probability depicts the behaviour of the driver at that moment. Also represented on the dashboard is the driver agent actions that shows the action to be taken. The actions are in two sets, where the first set provides indicator on speeding i.e. accelerate, decelerate or stop as the second sets provides indicators on cornering actions i.e. turn right, turn left or move on. At the bottom of the dashboard is a map with a marker showing the exact position of the vehicle. The dashboard data values for both the human driver and the driver agent refresh at an interval of 1000 milliseconds.

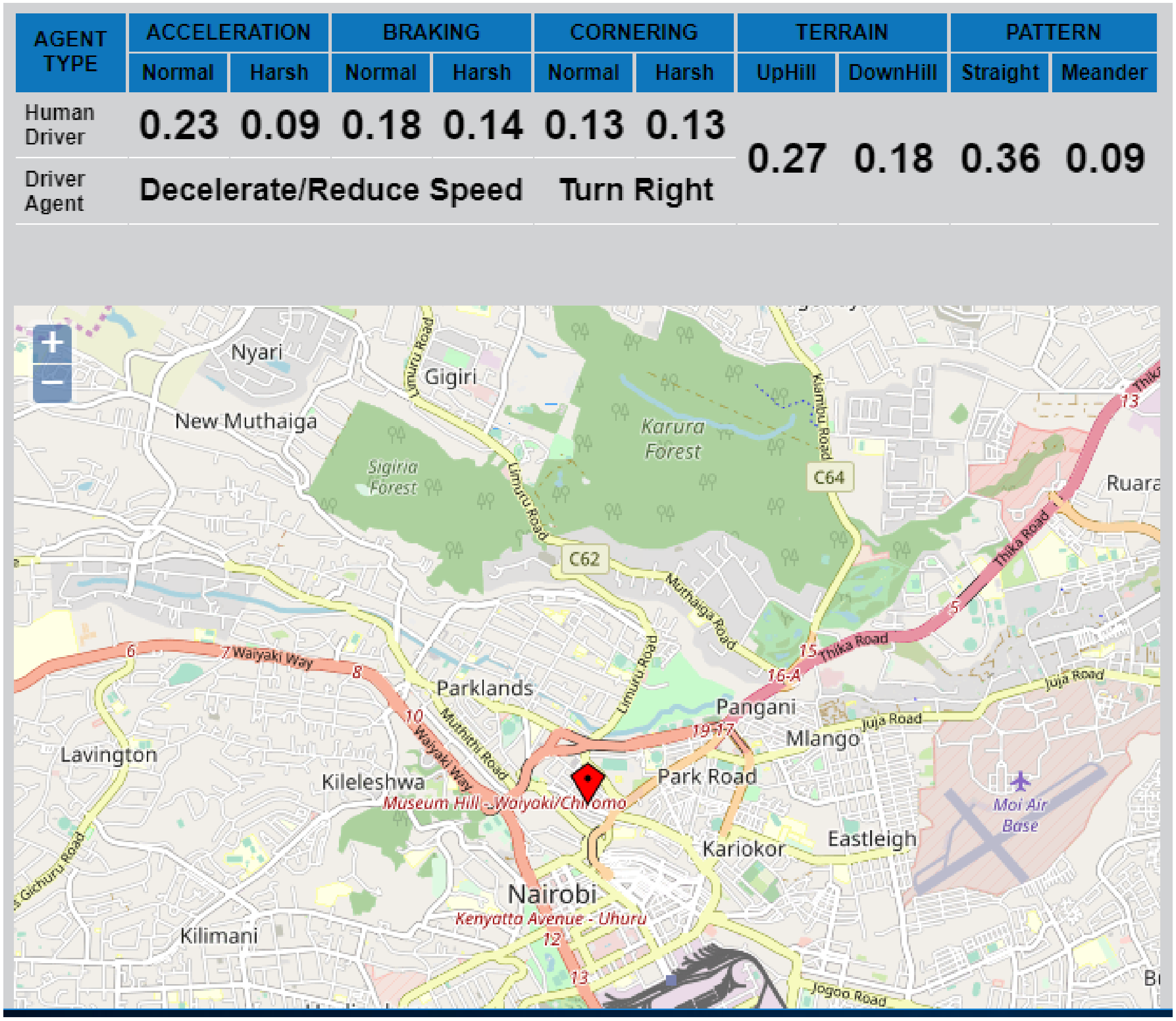


Figure 4.22. Human Agent Verses Vehicle Driver Agent Dashboard

4.3.3.2 VALIDATION AND TESTING OF THE DRIVER AGENT

Agent testing was done under different road segments and conditions to ascertain stability. The test environments encompassed roads with different states and patterns, dual and single carriageways of different lengths and under varied times of the day and weather conditions. The agent actions were evaluated against actions of the human vehicle driver. The variations in environment types accommodated the fact that vehicle drivers operate under diverse, and dynamic environments during which their actions may vary. One such an example is as outlined in Figure 4.23 for a journey from Tuala to Langata. The road was composed of 90% single carriageway with the remaining part being a dual carriageway. It had some uphill and downhill sections, straight stretches and corners, with the experiment being carried out at daytime. The location was a suitable choice since it represented a set of varied features that characterize the operational environments of human vehicle drivers.

The test driver was chosen among the drivers that were used to formulate the training data set. The driver had a valid driving license, a sign that he/she was legally permitted to drive vehicles on Kenyan roads.

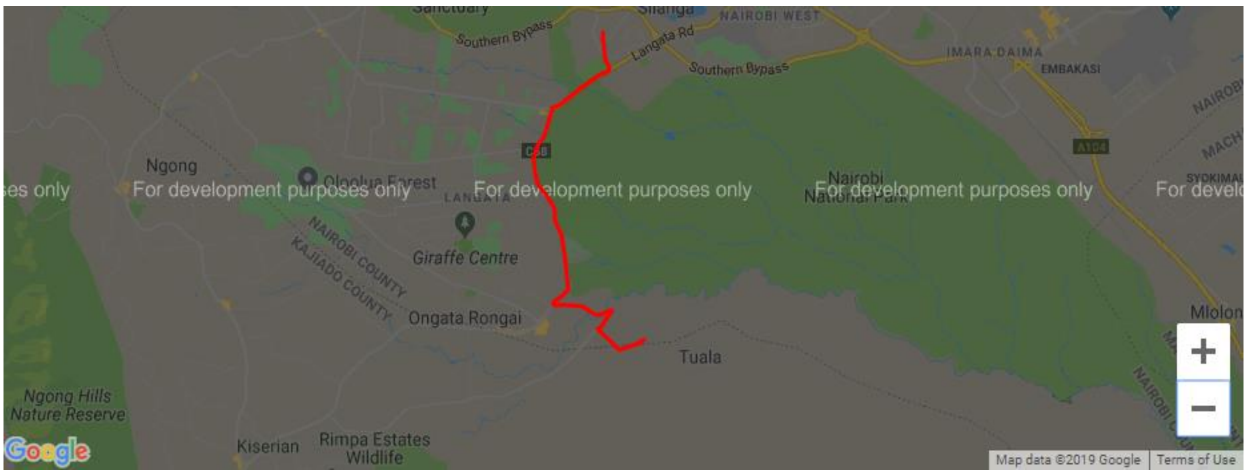


Figure 4.23. Driver Agent Test Environment

Table 0.16 under Appendix F shows sample data collected from a human vehicle driver on the same route. This is part of the data that was used to train the driver agent. During agent training on the route, several data points were logged in the agent training table in the database. Table 0.17 under Appendix F shows the data points for the sample route. Each data point formed the center of a Gaussian that would inform the driver agent on the actions to take.

After agent training based on the training set, agent actions were now recorded on the route. Table 4.42 shows actions of the driver agent at every point for half of the journey where the speeding, cornering and terrain indicate the actions of the driver agent based on its percepts. The agent operates as a software agent such that as the human vehicle driver was on the wheel, the driver agent was indicating its actions on the dashboard at periodical intervals of 1000 milliseconds.

Table 4.42. Agent Actions Testing

	Location		Human Driver Actions				Driver Agent Actions			
DBID	LAT	LON	Δ SPEED	Δ TIME	Δ ALT	Δ DIR	SPEEDING	CORNERING	TERRAIN	RATE
3	-1.39172	36.77649	15	38	-25	-40	Accelerate/Speed	Turn Left	Rolling	0
4	-1.39173	36.77652	5	25	-23	-96	Accelerate/Speed	Turn Left	Rolling	0
5	-1.39173	36.77652	5	25	-23	-96	Accelerate/Speed	Turn Left	Rolling	0
6	-1.39173	36.77652	5	25	-23	-96	Accelerate/Speed	Turn Left	Rolling	0
7	-1.3917	36.7765	5	25	-23	-96	Accelerate/Speed	Turn Left	Rolling	0
8	-1.39186	36.77631	15	38	-25	-40	Accelerate/Speed	Turn Left	Rolling	0
9	-1.39185	36.77624	15	38	-25	-40	Accelerate/Speed	Turn Left	Rolling	0
10	-1.39171	36.77596	15	38	-25	-40	Decelerate/Reduce Speed	Turn Left	Rolling	0
11	-1.39147	36.77549	8	40	-23	0	Decelerate/Reduce Speed	Straight Stretch	Flat	0
12	-1.3911	36.77428	-4	46	9	34	Decelerate/Reduce Speed	Turn Right	Climbing	0
13	-1.39106	36.77379	5	53	23	54	Accelerate/Speed	Turn Right	Climbing	0
14	-1.39103	36.7733	5	53	23	54	Accelerate/Speed	Turn Right	Climbing	0
15	-1.39103	36.77276	28	44	29	51	Accelerate/Speed	Turn Right	Climbing	0
16	-1.39099	36.77229	19	35	21	42	Decelerate/Reduce Speed	Turn Right	Rolling	0
17	-1.39088	36.77123	-1	20	13	-5	Decelerate/Reduce Speed	Turn Left	Rolling	0
18	-1.39073	36.76956	-4	27	14	-27	Accelerate/Speed	Turn Left	Rolling	0
19	-1.39076	36.76909	-5	40	9	-27	Accelerate/Speed	Turn Left	Rolling	0
20	-1.3908	36.76859	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
21	-1.39084	36.76809	1	34	3	-9	Accelerate/Speed	Turn Left	Climbing	0
22	-1.39081	36.76756	1	34	3	0	Accelerate/Speed	Straight Stretch	Climbing	0
23	-1.39056	36.76699	4	34	3	1	Accelerate/Speed	Turn Right	Climbing	0
24	-1.3905	36.76697	4	34	3	1	Accelerate/Speed	Turn Right	Climbing	0
25	-1.3904	36.767	4	34	3	1	Accelerate/Speed	Turn Right	Climbing	0
26	-1.39011	36.76721	4	34	3	1	Decelerate/Reduce Speed	Turn Right	Climbing	0
27	-1.38974	36.76753	1	34	3	0	Decelerate/Reduce Speed	Straight Stretch	Climbing	0
28	-1.3894	36.76785	1	34	3	0	Decelerate/Reduce Speed	Straight Stretch	Climbing	0
29	-1.38912	36.76827	1	34	3	-9	Accelerate/Speed	Turn Left	Climbing	0
30	-1.38893	36.76875	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
31	-1.38869	36.76922	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
32	-1.38833	36.76957	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
33	-1.38787	36.77005	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
34	-1.38737	36.77054	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
35	-1.38697	36.77087	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
36	-1.38653	36.77107	1	34	3	0	Accelerate/Speed	Straight Stretch	Rolling	0
37	-1.38607	36.77112	36	41	-8	-226	Accelerate/Speed	Turn Left	Rolling	0
38	-1.38554	36.77107	36	41	-8	-226	Accelerate/Speed	Turn Left	Rolling	0
39	-1.38501	36.77099	43	29	-8	-266	Accelerate/Speed	Turn Left	Rolling	0

4.3.3.3 EVALUATION OF THE DRIVER AGENT

The road segment had several turns or corners in the beginning. However, a good part of the road was straight with gentle turns. Other corners were towards the end of the journey. From the results for half of the journey as presented in Table 4.42, it is evident that the driver agent was able to detect these corners and advised for turning as its recorded and displayed actions. Instances of a hill climb and rolling were also correctly detected as these are physically present on the road. The agent also advised on instances that required acceleration or deceleration. The rate parameter gives room for human intervention as a way to reward the agent for good actions taken. A complete set of agent actions for the entire journey is as outlined in Table 0.18 under Appendix F. Figure 4.24 presents confusion matrices for acceleration, cornering and road terrain actions of the agent in comparison to the actions by the human vehicle driver for the complete journey. Performance of the agent was evaluated against four different measures, namely, accuracy, precision, recall and F-score. This was based on four different elements that form the confusion matrix i.e. True Positive (Tp), True Negative (Tn), False Positive (Fp) and False Negative (Fn).

Accuracy is a numeric measure of how good an algorithm is. It represents how many correct results the agent managed to identify, which is the proportion of true results among the total number of cases that are examined. This was computed using equation (19).

$$\text{Accuracy} = (Tp+Tn)/(Tp+Tn+Fp+Fn) \tag{19}$$

Precision represents the fraction of agent actions that are relevant. This was computed using equation (20).

$$\text{Precision} = Tp/(Tp+Fp) \tag{20}$$

Recall represents the fraction of agent actions that were undertaken. This was computed using equation (21).

$$\text{Recall} = Tp/(Tp+Fn) \tag{21}$$

F-score is a tradeoff of precision against recall. The higher the F-score value, the better the algorithm. This was computed using equation (22).

$$\text{F-Score} = 2*\text{Precision}*\text{Recall}/(\text{Precision} + \text{Recall}) \tag{22}$$

Acceleration Evaluation

		Human Driver P	Human Driver N
Driver Agent	P	57	0
	N	26	0

Accuracy = *0.687*
Precision = *1.000*
Recall = *0.687*
F-score = *0.814*

Cornering Evaluation

		Human Driver P	Human Driver N
Driver Agent	P	46	0
	N	37	0

Accuracy = *0.554*
Precision = *1.000*
Recall = *0.554*
F-score = *0.713*

Terrain Evaluation

		Human Driver P	Human Driver N
Driver Agent	P	45	0
	N	38	0

Accuracy = *0.542*
Precision = *1.000*
Recall = *0.542*
F-score = *0.703*

Figure 4.24 Confusion Matrices for Agent Testing

The driver agent test results clearly show the fact that the agent was able to display correct actions under the three categories. For instance, acceleration actions were successfully detected at accuracies of 68.7% while cornering and terrain action accuracies stood at 55.4% and 54.2% respectively. The lower accuracy rate for terrain actions was attributed to the fact that the agent was not flagging flat regions properly. Similarly, the agent was not flagging straight stretches properly for cornering actions, hence the low accuracy rate. The success that was above 50% in all cases is an indicator that probabilistic reasoning methodologies used properly determined the vehicle driver behaviour leading to the formulation of a valid driver behaviour dataset. In addition, all the three measures recorded an F-score value of over 70%, an indicator that the algorithms used by the agent were appropriately good.

4.3.3.4 DRIVER AGENT MODEL

Figure 4.25 summarises how the agent operates. The agent's state keeps changing as the journey goes on. On the same note, its plan, context and actions also change progressively. A reward is issued for agent actions that are commendable. This acts as a form of reinforcement learning with reward. Agent state, plan and actions loop due to the dynamic nature of a vehicle driver's operational environment.

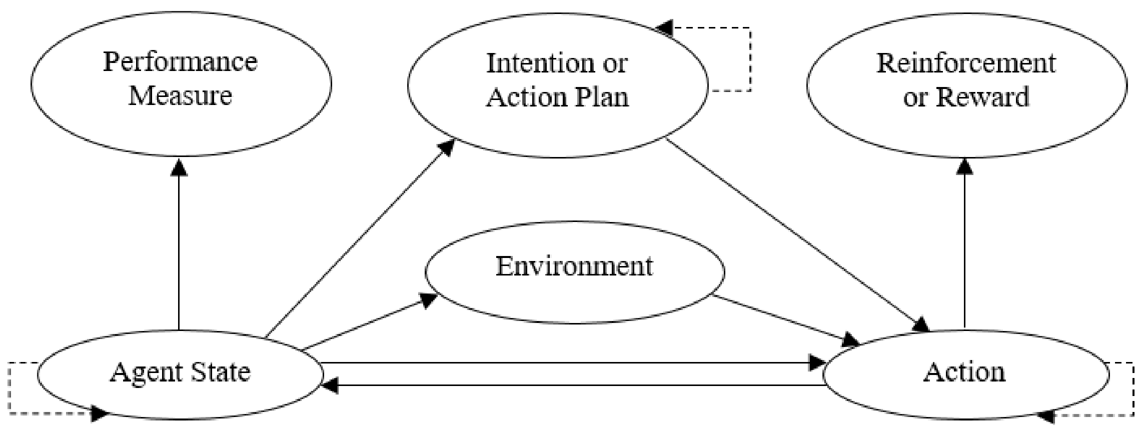


Figure 4.25. Driver Agent Model

4.4 SUMMARY OF STUDY FINDINGS

The findings in this chapter can hence be summarized as follows guided by the research objectives.

The first objective sought to investigate how we could monitor and analyse behavioural parameters for a human vehicle driver operating under diverse environments. This was looked at from three perspectives:

1. What parameters are required to determine vehicle driver behaviour?
2. How can these parameters be established, collected or monitored?
3. How can the collected parameters be analysed to determine the behaviour of the driver?

Driving styles may be characterized based on different factors that include overtaking, speeding, acceleration, braking, lane changing trends among others trends. It was determined that driver behaviour is based on different factors that formulate the required parameters or variables. These variables include speed, timestamp, latitude, longitude, altitude, direction (angle) and obstacle data. The combined use of a GPS system, vehicle mounted monitoring systems and a server application successfully facilitated the gathering and logging of these data parameters in real-time. However, obstacle detection was not 100% successful due to major limitations based on type of sensors used. From the findings, it is recommended that ultrasonic sensors could be replaced by other sensors at the expense of cost or alternatively, sensor fusion be applied. To determine the driver's driving style, stochastic or probabilistic reasoning methodologies are required. This led to the incorporation of special data analysis algorithms including, the Two-Timeslice Bayesian Network (2TBN), Expectation Maximisation and the Gaussian Mixture Model. The choice of these algorithms was due to the fact that the nature of the data required a time series kind of analysis. The main outcome of this objective was the determination of a vehicle driver's profiles during and after a given journey.

The second objective sought to formulate a dataset on driver behavioural patterns. This was achieved as an outcome of the profiles determined in the first objective. The collected and analysed data that determined driver behaviour was used to formulate a driver behaviour dataset. The dataset was built after numerous experiments that collected and analysed huge amounts of data from different drivers operating under different environments. Such a dataset could find many applications including informing future studies on transport and safety.

The last two objectives aimed at developing and evaluating a vehicle driver agent which can operate in a complex environment. The study considered the three key phases of an intelligent agent, namely, training, validation and testing. To achieve this, it was established that special algorithms have to be fused to complement one another. The operation of the software agent was hence founded on the Mixture Models, Factor Analysis, and Bayesian Inferencing. The Gaussian Mixture Model supported by the Expectation Miximisation were critical in the determination of agent action based on learning and other factors in its environment. The software driver agent successfully operated in parallel with a human vehicle driver. The agent's actions displayed on the dashboard determined its performance.

Based on the findings, the study hypothesis stands accepted that "a utility-based agent can be used as a basis for modelling human vehicle driver behaviour".

Table 4.43 outlines a summary of the benchmark for the resulting model against an existing closely related model, the UTDrive model.

Table 4.43. Model Benchmarking

	Existing Models (UTDrive Platform)	**The Model in this Study**
Motivation	A research platform for in-vehicle safety systems and driver behaviour modelling	A platform for driver behaviour modelling and operational environment detection
Selected Key Features	▪ Focused more on an in-vehicle environment driver behaviour detection. ▪ Can detect driver stress levels and in-vehicle distractions. ▪ The corpus used was gender sensitive.	▪ Purely focused on an out-vehicle environment driver behaviour detection. ▪ Predicts operational environment: terrain and pattern. ▪ Includes a driver agent for driver assistance.
Methodology	Use of a mixture of algorithms due to the incorporation of numerous sensors.	Use of probabilistic reasoning and intelligence methodologies: ▪ Bayesian Networks ▪ Gaussian Mixture Models

4.5 SUMMARY

The chapter outlined and discussed research findings with respect to the study objectives, research questions and hypothesis. The next chapter concludes the study with recommendations for further studies.

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

This chapter outlines the overall study conclusion and recommendations. Chapter content is presented under three main sections, namely, conclusions, recommendations for further research and recommendations for policy and practice.

5.1 CONCLUSION

Safety of road users is paramount globally with many renown organisations like the World Health Organisation and the International Traffic Safety Data and Analysis Group advocating for measures to reduce traffic injuries resulting from road accidents. Four main factors contribute to road accidents, namely, structures of roads, states of roads, states of vehicles and behaviour of vehicle drivers. A review of literature determined human vehicle driver behaviour as the major cause of road accidents globally. Unfortunately, this happens to be the factor that has so far proven to be the most difficult to monitor, analyse and model. This study established that driver behaviour can be modelled using a utility-based agent where the research outcome showed that the utility-based agent achieved mean performance accuracy rate of over 68%, +/- 5. This was a clear indicator that probabilistic methodologies used correctly determined the vehicle driver behaviour leading to the formulation of a valid driver behaviour dataset. Agent mean evaluation F-score values of over 70%, +/-5 for detection of operational environments with respect to corners and terrains and F-score values of over 80%, +/-5 for acceleration action were further confirmations on the appropriateness of the algorithms used by the agent. These successful study outcomes are an affirmation on the study hypothesis that a utility-based agent can be used as a basis for modelling human vehicle driver behaviour.

5.2 RECOMMENDATIONS FOR FURTHER RESEARCH

5.2.1 RECOMMENDATIONS MADE DIRECTLY FROM DATA

Reliance on GPS data parameters with statistical probabilistic reasoning methodologies offers a perfect approach for driver behaviour monitoring and analysis. Such analyses could be enhanced further if more data parameters could be captured. For instance, inclusion of On-Board

Diagnostics (OBD) vehicle data could enrich the scope and accuracy in the determination of driver behaviour. Further research should focus on full OBD data capture to complement GPS data. Appropriate obstacle sensing could further improve on the results of such a study.

5.2.2 RECOMMENDATIONS BASED ON CHALLENGES

The study recommends the use of other types of obstacle sensors as opposed to ultrasonic sensors for driver behaviour monitoring and profiling studies. This is centered on the major challenge of long range obstacle sensing that came up as a major limitation in this study. This was affected by the large beam width offered by ultrasonic sensors. To achieve better and reliable results in obstacle detection, two considerations could be put in place:

i) Use of Alternative Technologies

Alternative obstacle detection technologies could be used. For instance, the Radio Detection and Ranging (RADAR) and the laser-based Light Imaging Detection and Ranging (LIDAR). However, both technologies come with pros and cons. Both technologies use the concept of sending signals that bounce back upon hitting an obstacle, hence, the stronger the signal, the better the reflection. The distance to the object is calculated based on the time taken for each pulse to bounce back. RADAR technology is based on radio waves while laser-based LIDAR technology uses laser light waves. It is worth noting that radio waves travel further than sound waves and are undetectable to human sensory organs, as a result, they are best suited for long-range obstacle detection compared to sound waves used by ultrasonic sensors. Both radio and light waves have relatively same speeds though radio waves have less absorption compared to light waves, a factor that makes radio waves propagate well in relatively longer distances. Smart car makers prefer laser rangefinders since they are able to create a 3 dimensional image of the obstacle. This makes it possible to determine the exact size of an object. However, laser waves are affected by darkness and cloudy weather, hence, not suited for obstacle detection at night. In addition, the technology is more expensive than RADAR.

The development of a RADAR based obstacle detection and warning system was pushed ahead by Mercedes Benz in 90’s. Presently, automakers like Google, Uber, Tesla and Toyota use either or both radio and laser wave technologies in addition to cameras, ultrasonic and infrared technologies. RADAR technology is heavily used in airplanes, military vehicles, battleships and marine equipment for long range obstacle detection. This is due to its suitability to operate at daytime and nighttime and with less interference under varying weather conditions.

The frequency-modulated continuous-wave (FMCW) is an example of a RADAR technology that uses electromagnetic waves transmitted by a front-end antenna system with the reflected signal used to determine target distance and speed. The waves may be at microwave frequencies or higher frequencies. FMCW radar sensors can change their operating frequency during measurement, hence, the term frequency modulation. Such a technology is best suited for environments with poor visibility. The waves have the capability to penetrate mud and sprays and with an added advantage that allows for beam width adjustment to suite particular applications. On the other hand, laser rangefinders send focused laser light beams, suited for long range, high directionality and fast response time kinds of application scenarios. It is worth noting that Laser light is monochromatic, directional, and coherent such that it is one wavelength colour, with relatively narrow beams in one direction and the wavelengths are in phase in space and time. Hence, this may solve the problem of detections of the ground as an obstacle, as was the case for ultrasound waves. Unfortunately, laser lights are affected by poor environmental visibility. This disadvantages the use of the technology under certain conditions like muddy environments or environments with sprays. Unfortunately, rangefinders using either radio or laser technology come at a high cost compared to ultrasound and infrared based rangefinders.

ii) Sensor Fusion

Sensor fusion is a concept that entails combining two or more technologies such that they complement one another. For instance, if cost is a major issue, ultrasonic sensors could be combined with infrared sensors to offer the following advantages:

i) Ultrasonic sensors could complement infrared sensors that fail under poor lighting conditions such as smoke or fog and cannot detect transparent obstacles.
ii) On the other hand, infrared sensors could complement ultrasonic sensors that cannot appropriately detect sound absorbing or soft surfaces. Such a sensor fusion can be quite advantageous since both technologies are cheap as compared to other high cost technologies like radio and laser. Unfortunately, such a fusion is limited to mid-range

detection hence cannot detect obstacles at far distances. This is a major drawback for such a sensor fusion.

Radio waves and laser waves employed by RADAR and laser-based LIDAR sensors respectively could also be fused to complement one another. This is best suited in cases where cost is not a limiting factor. High accuracy, precision and reliability in obstacle detection could be achieved if different technologies like radio waves, laser waves, ultrasonic waves and infrared waves could all be fused. This kind of fusion is already being embraced by modern day automakers working on smart cars. It is worth mentioning that the fusion is further enhanced by the use of sophisticated cameras and data and image processing algorithms. Further research could explore on the use of laser range sensing technology, a kind of technology heavily employed in the Google self-driving car project and other smart car projects.

A proper and well-thought sensor fusion complemented by cameras and appropriate data processing algorithms will definitely mitigate most of the challenges in obstacle detection. This will address the cases of failed detections experienced particularly when both the sensor and obstacles are in motion and when obstacles have differing unpredictable surface properties since the different sensor technologies will complement one another's shortcomings.

5.3 RECOMMENDATIONS FOR POLICY AND PRACTICE

From the study, there was a strong indication that driver behaviour is a leading factor to road traffic injuries. This study therefore revealed issues that led to the following recommendations that should inform on policy and practice, particularly for developing nations to help achieve road safety through the adoption of the model:

1. There should be a mechanism in place for continuous monitoring of vehicle drivers' behaviour as they go along with their day to day activities on world roads. This should come in as a Governmental or Transport and Safety Authority policy.

2. The privacy policy should be reviewed to help accommodate the use of GPS technology for driver behaviour monitoring and profiling.

3. It is advocated that the driver behaviour monitoring and analysis model be incorporated in driver training schools. The model should also be a key tool that informs Traffic Departments on whether to issue a driving permit to new drivers or not. It should also be used in making decisions on possible revocations and/or cancelation of existing driving permits.

Full implementation of the model by Government agencies like the Transport and Safety Authorities would require a policy to be put in place such that all employees be trained on how to use the model. This would help in the understanding and utilisation of the data generated by use of the model.

The resulting utility-based agent for vehicle driver modelling could be visualised in three different perspectives, namely:

a) A model that establishes and profiles vehicle driver behaviour.
b) A dataset on vehicle driver behaviour.
c) A utility-based agent that models vehicle drivers.

Either of these study outcome perspectives could be adopted and implemented independently or all could be adopted and implemented simultaneously. For instance, stakeholders interested in determination of driver behaviour and profiling drivers based on their behaviour could only adopt and implement the model that establishes and profiles vehicle driver behaviour. Such stakeholders include but are not limited to insurance companies, transport and safety authorities, traffic departments of the police force, organisations with large fleets, cab companies among others. On the other hand, parties interested in Intelligent Transportation Systems for instance the self-driving car technologies will find the utility-based agent for vehicle driver modelling vital as a foundation worth exploration for extension.

Researchers and academia in the area of transport and driver behaviour will find the dataset on driver behaviour a great avenue for their studies. Such beneficiaries could also adopt and implement the model that determines and profiles vehicle drivers based on their behaviour. Such a move could allow them to generate their own datasets on driver behaviour for specific customized studies.

Adoption of either model or the full model could be supported or affected by several different factors. Table 5.1 outlines a suggestion of key factors that could aid or hinder adoption of the model in full. The rating per category of factors is based on the perception of the status of Kenya as a Nation. This hence means that the rating may vary after a full study on the adoption of the model is carried out.

Table 5.1. Factors that Could Aid or Hinder Adoption of the Model

	Factors	**Rating**
	Availability of supporting technology	30%
	Ease of use once implemented	30%
Aiding Factors	Low cost of required devices	20%
	Availability of skilled personnel	10%
	Key stakeholders support	10%
	Lack of modern day infrastructure	40%
	High cost of internet or data bundles	30%
Hindering Factors	Lack of trust in technology	10%
	Lack of policy on privacy	10%
	Enactment of National laws	10%

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APPENDICES

APPENDIX A: MICROCONTROLLER PROGRAM FOR PROXIMITY SENSORS

```
#define trigpin 2
#define echopin 3
#define gpstrigpin 4

void setup() {
Serial.begin(9600);
pinMode(trigpin, OUTPUT);
pinMode(echopin, INPUT);
pinMode(gpstrigpin, OUTPUT);
}

void loop() {
int distance, duration;
digitalWrite(trigpin, HIGH);
delayMicroseconds(1000);
digitalWrite(trigpin, LOW);
duration = pulseIn(echopin, HIGH);
distance = (duration/2)/29.1;
Serial.print(distance);
Serial.println(" cm");
delay(100);

if(distance>0 && distance<400){
digitalWrite(gpstrigpin, HIGH);
}
else{
digitalWrite(gpstrigpin, LOW);
}
}
```

APPENDIX B: BEHAVIOURAL PROBABILITIES

Table 0.1. Behaviour and Environment Probabilities per Driving State

	State					Behaviour						Environment			
	ΔAccl (m/s^2)	ΔTime (s)	ΔAlt (m)	ΔDir (^{0})	Obst	Normal Accel	Harsh Accel	Normal Braking	Harsh Braking	Normal Corner	Harsh Corner	Meander	Straight	Up-Hill	Down-Hill
1	0 - 5	<=5	0 - 5	<+/-45	Yes	0.25	0.10	0.18	0.17	0.15	0.15	0.10	0.40	0.40	0.10
2	0 - 5	<=5	0 - 5	<+/-45	No	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.40	0.10
3	0 - 5	<=5	0 - 5	>=+/-45	Yes	0.25	0.10	0.18	0.17	0.10	0.20	0.40	0.10	0.40	0.10
4	0 - 5	<=5	0 - 5	>=+/-45	No	0.20	0.15	0.20	0.15	0.10	0.20	0.40	0.10	0.40	0.10
5	0 - 5	<=5	> 5	<+/-45	Yes	0.27	0.08	0.23	0.12	0.15	0.15	0.10	0.40	0.50	0.00
6	0 - 5	<=5	> 5	<+/-45	No	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.50	0.00
7	0 - 5	<=5	> 5	>=+/-45	Yes	0.27	0.08	0.23	0.12	0.20	0.10	0.40	0.10	0.50	0.00
8	0 - 5	<=5	> 5	>=+/-45	No	0.25	0.10	0.25	0.10	0.20	0.10	0.40	0.10	0.50	0.00
9	0 - 5	<=5	-0 - -5	<+/-45	Yes	0.27	0.08	0.23	0.12	0.15	0.15	0.10	0.40	0.10	0.40
10	0 - 5	<=5	-0 - -5	<+/-45	No	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.10	0.40
11	0 - 5	<=5	-0 - -5	>=+/-45	Yes	0.27	0.08	0.23	0.12	0.10	0.20	0.40	0.10	0.10	0.40
12	0 - 5	<=5	-0 - -5	>=+/-45	No	0.25	0.10	0.25	0.10	0.10	0.20	0.40	0.10	0.10	0.40
13	0 - 5	<=5	< -5	<+/-45	Yes	0.22	0.13	0.18	0.17	0.15	0.15	0.10	0.40	0.00	0.50
14	0 - 5	<=5	< -5	<+/-45	No	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.00	0.50
15	0 - 5	<=5	< -5	>=+/-45	Yes	0.22	0.13	0.18	0.17	0.10	0.20	0.40	0.10	0.00	0.50
16	0 - 5	<=5	< -5	>=+/-45	No	0.20	0.15	0.20	0.15	0.10	0.20	0.40	0.10	0.00	0.50
17	0 - 5	>5	0 - 5	<+/-45	Yes	0.27	0.08	0.23	0.12	0.15	0.15	0.10	0.40	0.40	0.10
18	0 - 5	>5	0 - 5	<+/-45	No	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.40	0.10
19	0 - 5	>5	0 - 5	>=+/-45	Yes	0.27	0.08	0.23	0.12	0.12	0.18	0.40	0.10	0.40	0.10
20	0 - 5	>5	0 - 5	>=+/-45	No	0.25	0.10	0.25	0.10	0.12	0.18	0.40	0.10	0.40	0.10
21	0 - 5	>5	> 5	<+/-45	Yes	0.30	0.05	0.27	0.08	0.15	0.15	0.10	0.40	0.50	0.00
22	0 - 5	>5	> 5	<+/-45	No	0.28	0.07	0.28	0.07	0.15	0.15	0.10	0.40	0.50	0.00
23	0 - 5	>5	> 5	>=+/-45	Yes	0.30	0.05	0.27	0.08	0.12	0.18	0.40	0.10	0.50	0.00
24	0 - 5	>5	> 5	>=+/-45	No	0.28	0.07	0.28	0.07	0.12	0.18	0.40	0.10	0.50	0.00
25	0 - 5	>5	-0 - -5	<+/-45	Yes	0.30	0.05	0.27	0.08	0.15	0.15	0.10	0.40	0.10	0.40
26	0 - 5	>5	-0 - -5	<+/-45	No	0.28	0.07	0.28	0.07	0.15	0.15	0.10	0.40	0.10	0.40
27	0 - 5	>5	-0 - -5	>=+/-45	Yes	0.30	0.05	0.27	0.08	0.12	0.18	0.40	0.10	0.10	0.40
28	0 - 5	>5	-0 - -5	>=+/-45	No	0.28	0.07	0.28	0.07	0.12	0.18	0.40	0.10	0.10	0.40
29	0 - 5	>5	< -5	<+/-45	Yes	0.27	0.08	0.23	0.12	0.15	0.15	0.10	0.40	0.00	0.50
30	0 - 5	>5	< -5	<+/-45	No	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.00	0.50
31	0 - 5	>5	< -5	>=+/-45	Yes	0.27	0.08	0.23	0.12	0.12	0.18	0.40	0.10	0.00	0.50
32	0 - 5	>5	< -5	>=+/-45	No	0.25	0.10	0.25	0.10	0.12	0.18	0.40	0.10	0.00	0.50
33	>5	<=5	0 - 5	<+/-45	Yes	0.15	0.20	0.10	0.25	0.15	0.15	0.10	0.40	0.40	0.10
34	>5	<=5	0 - 5	<+/-45	No	0.07	0.28	0.07	0.28	0.15	0.15	0.10	0.40	0.40	0.10
35	>5	<=5	0 - 5	>=+/-45	Yes	0.15	0.20	0.10	0.25	0.10	0.20	0.40	0.10	0.40	0.10
36	>5	<=5	0 - 5	>=+/-45	No	0.07	0.28	0.07	0.28	0.10	0.20	0.40	0.10	0.40	0.10
37	>5	<=5	> 5	<+/-45	Yes	0.17	0.18	0.18	0.17	0.15	0.15	0.10	0.40	0.50	0.00
38	>5	<=5	> 5	<+/-45	No	0.10	0.25	0.15	0.20	0.15	0.15	0.10	0.40	0.50	0.00
39	>5	<=5	> 5	>=+/-45	Yes	0.17	0.18	0.18	0.17	0.10	0.20	0.40	0.10	0.50	0.00
40	>5	<=5	> 5	>=+/-45	No	0.10	0.25	0.15	0.20	0.10	0.20	0.40	0.10	0.50	0.00
41	>5	<=5	-0 - -5	<+/-45	Yes	0.17	0.18	0.18	0.17	0.15	0.15	0.10	0.40	0.10	0.40
42	>5	<=5	-0 - -5	<+/-45	No	0.10	0.25	0.15	0.20	0.15	0.15	0.10	0.40	0.10	0.40
43	>5	<=5	-0 - -5	>=+/-45	Yes	0.17	0.18	0.18	0.17	0.07	0.23	0.40	0.10	0.10	0.40
44	>5	<=5	-0 - -5	>=+/-45	No	0.10	0.25	0.15	0.20	0.07	0.23	0.40	0.10	0.10	0.40
45	>5	<=5	< -5	<+/-45	Yes	0.05	0.30	0.08	0.27	0.15	0.15	0.10	0.40	0.00	0.50
46	>5	<=5	< -5	<+/-45	No	0.07	0.28	0.07	0.28	0.15	0.15	0.10	0.40	0.00	0.50
47	>5	<=5	< -5	>=+/-45	Yes	0.05	0.30	0.08	0.27	0.05	0.25	0.40	0.10	0.00	0.50
48	>5	<=5	< -5	>=+/-45	No	0.07	0.28	0.07	0.28	0.05	0.25	0.40	0.10	0.00	0.50
49	>5	>5	0 - 5	<+/-45	Yes	0.15	0.20	0.17	0.18	0.15	0.15	0.10	0.40	0.40	0.10
50	>5	>5	0 - 5	<+/-45	No	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.40	0.10
51	>5	>5	0 - 5	>=+/-45	Yes	0.15	0.20	0.17	0.18	0.18	0.22	0.40	0.10	0.40	0.10
52	>5	>5	0 - 5	>=+/-45	No	0.10	0.25	0.10	0.25	0.18	0.22	0.40	0.10	0.40	0.10
53	>5	>5	> 5	<+/-45	Yes	0.17	0.18	0.17	0.18	0.15	0.15	0.10	0.40	0.50	0.00
54	>5	>5	> 5	<+/-45	No	0.16	0.19	0.15	0.20	0.15	0.15	0.10	0.40	0.50	0.00
55	>5	>5	> 5	>=+/-45	Yes	0.17	0.18	0.17	0.18	0.17	0.23	0.40	0.10	0.50	0.00
56	>5	>5	> 5	>=+/-45	No	0.16	0.19	0.15	0.20	0.17	0.23	0.40	0.10	0.50	0.00
57	>5	>5	-0 - -5	<+/-45	Yes	0.15	0.20	0.15	0.20	0.15	0.15	0.10	0.40	0.10	0.40
58	>5	>5	-0 - -5	<+/-45	No	0.15	0.20	0.15	0.20	0.15	0.15	0.10	0.40	0.10	0.40
59	>5	>5	-0 - -5	>=+/-45	Yes	0.15	0.20	0.15	0.20	0.10	0.20	0.40	0.10	0.10	0.40
60	>5	>5	-0 - -5	>=+/-45	No	0.15	0.20	0.15	0.20	0.10	0.20	0.40	0.10	0.10	0.40
61	>5	>5	< -5	<+/-45	Yes	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.00	0.50
62	>5	>5	< -5	<+/-45	No	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.00	0.50
63	>5	>5	< -5	>=+/-45	Yes	0.10	0.25	0.10	0.25	0.05	0.25	0.40	0.10	0.00	0.50
64	>5	>5	< -5	>=+/-45	No	0.10	0.25	0.10	0.25	0.05	0.25	0.40	0.10	0.00	0.50
65	-0 - -5	<=5	0 - 5	<+/-45	Yes	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.40	0.10
66	-0 - -5	<=5	0 - 5	<+/-45	No	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.40	0.10
67	-0 - -5	<=5	0 - 5	>=+/-45	Yes	0.20	0.15	0.20	0.15	0.20	0.10	0.40	0.10	0.40	0.10
68	-0 - -5	<=5	0 - 5	>=+/-45	No	0.20	0.15	0.20	0.15	0.20	0.10	0.40	0.10	0.40	0.10
69	-0 - -5	<=5	> 5	<+/-45	Yes	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.50	0.00

70	-0 - -5	<=5	> 5	<+/-45	No	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.50	0.00
71	-0 - -5	<=5	> 5	>=+/-45	Yes	0.25	0.10	0.25	0.10	0.27	0.03	0.40	0.10	0.50	0.00
72	-0 - -5	<=5	> 5	>=+/-45	No	0.25	0.10	0.25	0.10	0.27	0.03	0.40	0.10	0.50	0.00
73	-0 - -5	<=5	-0 - -5	<+/-45	Yes	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.10	0.40
74	-0 - -5	<=5	-0 - -5	<+/-45	No	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.10	0.40
75	-0 - -5	<=5	-0 - -5	>=+/-45	Yes	0.25	0.10	0.25	0.10	0.25	0.05	0.40	0.10	0.10	0.40
76	-0 - -5	<=5	-0 - -5	>=+/-45	No	0.25	0.10	0.25	0.10	0.25	0.05	0.40	0.10	0.10	0.40
77	-0 - -5	<=5	< -5	<+/-45	Yes	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.00	0.50
78	-0 - -5	<=5	< -5	<+/-45	No	0.20	0.15	0.20	0.15	0.15	0.15	0.10	0.40	0.00	0.50
79	-0 - -5	<=5	< -5	>=+/-45	Yes	0.20	0.15	0.20	0.15	0.20	0.10	0.40	0.10	0.00	0.50
80	-0 - -5	<=5	< -5	>=+/-45	No	0.20	0.15	0.20	0.15	0.20	0.10	0.40	0.10	0.00	0.50
81	-0 - -5	>5	0 - 5	<+/-45	Yes	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.40	0.10
82	-0 - -5	>5	0 - 5	<+/-45	No	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.40	0.10
83	-0 - -5	>5	0 - 5	>=+/-45	Yes	0.25	0.10	0.25	0.10	0.20	0.10	0.40	0.10	0.40	0.10
84	-0 - -5	>5	0 - 5	>=+/-45	No	0.25	0.10	0.25	0.10	0.20	0.10	0.40	0.10	0.40	0.10
85	-0 - -5	>5	> 5	<+/-45	Yes	0.30	0.05	0.30	0.05	0.15	0.15	0.10	0.40	0.50	0.00
86	-0 - -5	>5	> 5	<+/-45	No	0.30	0.05	0.30	0.05	0.15	0.15	0.10	0.40	0.50	0.00
87	-0 - -5	>5	> 5	>=+/-45	Yes	0.30	0.05	0.30	0.05	0.27	0.03	0.40	0.10	0.50	0.00
88	-0 - -5	>5	> 5	>=+/-45	No	0.30	0.05	0.30	0.05	0.27	0.03	0.40	0.10	0.50	0.00
89	-0 - -5	>5	-0 - -5	<+/-45	Yes	0.30	0.05	0.30	0.05	0.15	0.15	0.10	0.40	0.10	0.40
90	-0 - -5	>5	-0 - -5	<+/-45	No	0.30	0.05	0.30	0.05	0.15	0.15	0.10	0.40	0.10	0.40
91	-0 - -5	>5	-0 - -5	>=+/-45	Yes	0.30	0.05	0.30	0.05	0.25	0.05	0.40	0.10	0.10	0.40
92	-0 - -5	>5	-0 - -5	>=+/-45	No	0.30	0.05	0.30	0.05	0.25	0.05	0.40	0.10	0.10	0.40
93	-0 - -5	>5	< -5	<+/-45	Yes	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.00	0.50
94	-0 - -5	>5	< -5	<+/-45	No	0.25	0.10	0.25	0.10	0.15	0.15	0.10	0.40	0.00	0.50
95	-0 - -5	>5	< -5	>=+/-45	Yes	0.25	0.10	0.25	0.10	0.20	0.10	0.40	0.10	0.00	0.50
96	-0 - -5	>5	< -5	>=+/-45	No	0.25	0.10	0.25	0.10	0.20	0.10	0.40	0.10	0.00	0.50
97	< -5	<=5	0 - 5	<+/-45	Yes	0.05	0.30	0.05	0.30	0.15	0.15	0.10	0.40	0.40	0.10
98	< -5	<=5	0 - 5	<+/-45	No	0.05	0.30	0.05	0.30	0.15	0.15	0.10	0.40	0.40	0.10
99	< -5	<=5	0 - 5	>=+/-45	Yes	0.05	0.30	0.05	0.30	0.20	0.10	0.40	0.10	0.40	0.10
100	< -5	<=5	0 - 5	>=+/-45	No	0.05	0.30	0.05	0.30	0.20	0.10	0.40	0.10	0.40	0.10
101	< -5	<=5	> 5	<+/-45	Yes	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.50	0.00
102	< -5	<=5	> 5	<+/-45	No	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.50	0.00
103	< -5	<=5	> 5	>=+/-45	Yes	0.10	0.25	0.10	0.25	0.27	0.03	0.40	0.10	0.50	0.00
104	< -5	<=5	> 5	>=+/-45	No	0.10	0.25	0.10	0.25	0.27	0.03	0.40	0.10	0.50	0.00
105	< -5	<=5	-0 - -5	<+/-45	Yes	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.10	0.40
106	< -5	<=5	-0 - -5	<+/-45	No	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.10	0.40
107	< -5	<=5	-0 - -5	>=+/-45	Yes	0.10	0.25	0.10	0.25	0.25	0.05	0.40	0.10	0.10	0.40
108	< -5	<=5	-0 - -5	>=+/-45	No	0.10	0.25	0.10	0.25	0.25	0.05	0.40	0.10	0.10	0.40
109	< -5	<=5	< -5	<+/-45	Yes	0.05	0.30	0.05	0.30	0.15	0.15	0.10	0.40	0.00	0.50
110	< -5	<=5	< -5	<+/-45	No	0.05	0.30	0.05	0.30	0.15	0.15	0.10	0.40	0.00	0.50
111	< -5	<=5	< -5	>=+/-45	Yes	0.05	0.30	0.05	0.30	0.20	0.10	0.40	0.10	0.00	0.50
112	< -5	<=5	< -5	>=+/-45	No	0.05	0.30	0.05	0.30	0.20	0.10	0.40	0.10	0.00	0.50
113	< -5	>5	0 - 5	<+/-45	Yes	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.40	0.10
114	< -5	>5	0 - 5	<+/-45	No	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.40	0.10
115	< -5	>5	0 - 5	>=+/-45	Yes	0.10	0.25	0.10	0.25	0.20	0.10	0.40	0.10	0.40	0.10
116	< -5	>5	0 - 5	>=+/-45	No	0.10	0.25	0.10	0.25	0.20	0.10	0.40	0.10	0.40	0.10
117	< -5	>5	> 5	<+/-45	Yes	0.15	0.20	0.15	0.20	0.15	0.15	0.10	0.40	0.50	0.00
118	< -5	>5	> 5	<+/-45	No	0.15	0.20	0.15	0.20	0.15	0.15	0.10	0.40	0.50	0.00
119	< -5	>5	> 5	>=+/-45	Yes	0.15	0.20	0.15	0.20	0.27	0.03	0.40	0.10	0.50	0.00
120	< -5	>5	> 5	>=+/-45	No	0.15	0.20	0.15	0.20	0.27	0.03	0.40	0.10	0.50	0.00
121	< -5	>5	-0 - -5	<+/-45	Yes	0.15	0.20	0.15	0.20	0.15	0.15	0.10	0.40	0.10	0.40
122	< -5	>5	-0 - -5	<+/-45	No	0.15	0.20	0.15	0.20	0.15	0.15	0.10	0.40	0.10	0.40
123	< -5	>5	-0 - -5	>=+/-45	Yes	0.15	0.20	0.15	0.20	0.25	0.05	0.40	0.10	0.10	0.40
124	< -5	>5	-0 - -5	>=+/-45	No	0.15	0.20	0.15	0.20	0.25	0.05	0.40	0.10	0.10	0.40
125	< -5	>5	< -5	<+/-45	Yes	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.00	0.50
126	< -5	>5	< -5	<+/-45	No	0.10	0.25	0.10	0.25	0.15	0.15	0.10	0.40	0.00	0.50
127	< -5	>5	< -5	>=+/-45	Yes	0.10	0.25	0.10	0.25	0.20	0.10	0.40	0.10	0.00	0.50
128	< -5	>5	< -5	>=+/-45	No	0.10	0.25	0.10	0.25	0.20	0.10	0.40	0.10	0.00	0.50

APPENDIX C: DATABASE SCHEMA

ts_admin

Field	Type	Null	Default
AdminId	int(11)	No	
Username	varchar(20)	No	
Password	varchar(20)	No	
FName	varchar(20)	No	
LName	varchar(20)	No	
Name	varchar(50)	No	
Photo	varchar(500)	No	
SuperAdminId	int(11)	No	
Status	smallint(6)	No	
RoleId	smallint(6)	No	

ts_agenttesting

Field	Type	Null	Default
dbID	int(11)	No	
AssetUID	varchar(20)	No	
Lat	float(9,6)	No	
Lon	float(9,6)	No	
GPSTime	int(11)	No	
Speed	int(11)	No	
ChgSpeed	float	No	
ChgTime	int(11)	No	
ChgAlt	int(11)	No	
ChgDir	smallint(6)	No	
AgentSpeeding	varchar(30)	No	
AgentCornering	varchar(30)	No	
AgentTerrain	varchar(30)	No	
Distance	float	Yes	NULL
Rate	smallint(6)	No	

ts_agenttraining

Field	Type	Null	Default
dbID	int(11)	No	
AssetUID	varchar(20)	No	
Lat	float(9,6)	No	
Lon	float(9,6)	No	
Speed	int(11)	No	
ChgSpeed	int(11)	No	
ChgTime	int(11)	No	
ChgAlt	int(11)	No	
ChgDir	smallint(6)	No	
avgnormaccl	float(3,3)	No	
avgharshaccl	float(3,3)	No	
avgnormbrake	float(3,3)	No	
avgharshbrake	float(3,3)	No	
avgnormcorner	float(3,3)	No	
avgharshcorner	float(3,3)	No	
avgmeander	float(3,3)	No	
avgstraight	float(3,3)	No	
avguphill	float(3,3)	No	
avgdownhill	float(3,3)	No	

ts_asset

Field	Type	Null	Default
dbID	int(11)	No	
AssetReg	varchar(20)	No	
AssetUID	varchar(20)	No	
AssetGSM	varchar(20)	Yes	NULL
AssetType	varchar(30)	Yes	NULL
AssetModel	varchar(30)	Yes	NULL
MileageInit	int(11)	Yes	NULL
LicenseNo	varchar(50)	No	
GroupId	int(11)	No	
AdminID	int(11)	No	
Photo	varchar(500)	No	
Status	smallint(6)	No	

ts_driver

Field	Type	Null	Default
LicenseNo	varchar(50)	No	
FName	varchar(50)	No	
LName	varchar(20)	No	
Dob	date	No	
LicenseExpDate	date	No	
CellNo	varchar(15)	No	
DriverEmail	varchar(50)	No	
Photo	varchar(500)	No	
AdminId	int(11)	No	

ts_driverbehaviour

Field	Type	Null	Default
dbID	int(11)	No	
AssetUID	varchar(20)	No	
PrevTime	int(11)	No	
CurTime	int(11)	No	
PrevSpeed	int(11)	No	
CurSpeed	int(11)	No	
PrevAlt	float	No	
CurAlt	float	No	
PrevDir	smallint(6)	No	
CurDir	smallint(6)	No	
PrevObst	smallint(6)	No	
CurObst	smallint(6)	No	
ChgAccl	float	No	
ChgTime	int(11)	No	
ChgAlt	float	No	
ChgDir	smallint(6)	No	
NormAccl	float	No	
HarshAccl	float	No	
NormBrake	float	No	
HarshBrake	float	No	
NormCorner	float	No	
HarshCorner	float	No	
Meander	float	No	
Straight	float	No	
UpHill	float	No	
DownHill	float	No	

ts_group

Field	Type	Null	Default
GroupId	int(11)	No	
GroupName	varchar(100)	No	
Description	varchar(500)	No	
UserId	int(11)	No	
AdminID	int(11)	No	
Photo	varchar(500)	No	

ts_lastpositionlog

Field	Type	Null	Default
dbID	int(11)	No	
AssetUID	varchar(20)	No	
GPSState	tinyint(4)	Yes	NULL
GPSTime	int(11)	No	
Lon	float(9,6)	Yes	NULL
Lat	float(9,6)	Yes	NULL
Speed	tinyint(4)	Yes	NULL
Direction	smallint(6)	Yes	NULL
EngineState	smallint(6)	Yes	NULL
Mileage	int(11)	Yes	NULL
Altitude	float(9,2)	Yes	NULL
Hdop	float(9,2)	Yes	NULL
Address	varchar(500)	Yes	NULL
LicenseNo	varchar(50)	Yes	NULL

ts_positionlog

Field	Type	Null	Default
dbID	int(11)	No	
AssetUID	varchar(20)	No	
GPSState	tinyint(4)	Yes	NULL
GPSTime	int(11)	No	
Lon	float(9,6)	Yes	NULL
Lat	float(9,6)	Yes	NULL
Speed	tinyint(4)	Yes	NULL
Direction	smallint(6)	Yes	NULL
EngineState	smallint(6)	Yes	NULL
Mileage	int(11)	Yes	NULL
Altitude	float(9,2)	Yes	NULL
Hdop	float(9,2)	Yes	NULL
IOState	int(11)	Yes	NULL
Address	varchar(500)	Yes	NULL
LicenseNo	varchar(50)	Yes	NULL

ts_user

Field	Type	Null	Default
UserId	int(11)	No	
Username	varchar(20)	No	
Password	varchar(20)	No	
FName	varchar(20)	No	
LName	varchar(20)	No	
Email	varchar(50)	No	
PhoneNo	varchar(13)	No	
Photo	varchar(500)	No	
AdminId	int(11)	No	
Status	smallint(6)	No	
RoleId	smallint(6)	No	

APPENDIX D: SAMPLE PRESTUDY DATA

Table 0.2. Sample Data for a Test Segment in Figure 4.1 (Prestudy)

Data Point	Driver	Lat	Lon	Spd (km/h)	Alt	Dir	Dir (^{0})	Time	GPSTime	GPS Signal Strength	Spd (m/s)	ΔSpd (m/s^2)	ΔDir (^{0})	ΔAlt (m)	ΔTm (s)	Accel/ Decel (m/s^2)
1	D1	-1.291865	36.825642	0	1474.2	N	0	1/19/2018 10:14	1516346042	7.1	0					
2	D1	-1.291808	36.825451	4	1659	NE	40	1/19/2018 10:14	1516346052	7.1	1.11	1.11	40	184.8	10	0.11
3	D1	-1.291725	36.82547	9	1658.5	NW	359	1/19/2018 10:14	1516346058	7.2	2.5	1.39	319	-0.5	6	0.23
4	D1	-1.291637	36.825451	7	1658	NW	348	1/19/2018 10:14	1516346062	7.2	1.94	-0.56	-11	-0.5	4	-0.14
5	D1	-1.291383	36.825264	4	1669.8	NW	308	1/19/2018 10:14	1516346077	7.2	1.11	-0.83	-40	11.8	15	-0.06
6	D1	-1.29143	36.82542	0	1665.9	NW	314	1/19/2018 10:14	1516346083	7.2	0	-1.11	6	-3.9	6	-0.19
7	D1	-1.291445	36.825455	0	1660.6	NW	314	1/19/2018 10:14	1516346093	7.3	0	0	0	-5.3	10	0
8	D1	-1.291427	36.825546	6	1658.6	NE	66	1/19/2018 10:15	1516346103	7.3	1.67	1.67	-248	-2	10	0.17
9	D1	-1.291498	36.825569	2	1667	SE	144	1/19/2018 10:15	1516346112	7.3	0.56	-1.11	78	8.4	9	-0.12
10	D1	-1.291502	36.825611	0	1673.5	SE	167	1/19/2018 10:15	1516346123	7.4	0	-0.56	23	6.5	11	-0.05
11	D1	-1.291463	36.825794	5	1666	NE	68	1/19/2018 10:15	1516346132	7.4	1.39	1.39	-99	-7.5	9	0.15
12	D1	-1.291317	36.825787	11	1665	NE	17	1/19/2018 10:15	1516346137	7.4	3.06	1.67	-51	-1	5	0.33
13	D1	-1.291128	36.825779	13	1665	NW	358	1/19/2018 10:15	1516346141	7.4	3.61	0.55	341	0	4	0.14
14	D1	-1.290865	36.825661	20	1671.1	NW	339	1/19/2018 10:15	1516346146	7.5	5.56	1.95	-19	6.1	5	0.39
15	D1	-1.290538	36.825336	21	1682.1	NW	329	1/19/2018 10:15	1516346151	3.7	5.83	0.27	-10	11	5	0.05
16	D1	-1.290403	36.825214	14	1686.9	NW	311	1/19/2018 10:15	1516346156	7.5	3.89	-1.94	-18	4.8	5	-0.39
17	D1	-1.290417	36.824944	22	1699.4	SW	264	1/19/2018 10:16	1516346163	7.5	6.11	2.22	-47	12.5	7	0.32
18	D1	-1.290852	36.824139	45	1704.4	SW	242	1/19/2018 10:16	1516346171	7.6	12.5	6.39	-22	5	8	0.8
19	D1	-1.291152	36.823692	51	1701.7	SW	240	1/19/2018 10:16	1516346175	7.6	14.17	1.67	-2	-2.7	4	0.42
20	D1	-1.291442	36.823219	54	1697.3	SW	239	1/19/2018 10:16	1516346179	7.6	15	0.83	-1	-4.4	4	0.21
21	D1	-1.291693	36.822746	48	1691.8	SW	242	1/19/2018 10:16	1516346183	7.6	13.33	-1.67	3	-5.5	4	-0.42
22	D1	-1.291905	36.822411	36	1686.5	SW	240	1/19/2018 10:16	1516346187	7.6	10	-3.33	-2	-5.3	4	-0.83
23	D1	-1.292103	36.822083	7	1678.1	SW	251	1/19/2018 10:16	1516346201	7.7	1.94	-8.06	11	-8.4	14	-0.58
24	D1	-1.292215	36.821957	9	1675.8	SW	219	1/19/2018 10:16	1516346213	7.7	2.5	0.56	-32	-2.3	12	0.05
25	D1	-1.292343	36.821873	10	1673.1	SW	219	1/19/2018 10:17	1516346220	7.8	2.78	0.28	0	-2.7	7	0.04
26	D1	-1.292442	36.821701	19	1672.9	SW	229	1/19/2018 10:17	1516346224	7.8	5.28	2.5	10	-0.2	4	0.63
27	D1	-1.29262	36.821445	25	1670	SW	231	1/19/2018 10:17	1516346228	7.8	6.94	1.66	2	-2.9	4	0.42
28	D1	-1.292905	36.82082	26	1656.2	SW	235	1/19/2018 10:17	1516346238	7.8	7.22	0.28	4	-13.8	10	0.03
29	D1	-1.293172	36.820782	18	1659.1	SE	172	1/19/2018 10:17	1516346244	7.9	5	-2.22	-63	2.9	6	-0.37
30	D1	-1.293417	36.820885	28	1660.3	SE	162	1/19/2018 10:17	1516346248	7.9	7.78	2.78	-10	1.2	4	0.7
31	D1	-1.294803	36.821705	34	1661.3	SE	153	1/19/2018 10:17	1516346262	2.2	9.44	1.66	-9	1	14	0.12
32	D1	-1.295043	36.821838	1	1662	SE	161	1/19/2018 10:17	1516346274	1.4	0.28	-9.16	8	0.7	12	-0.76
33	D1	-1.295222	36.821918	24	1670.2	SE	149	1/19/2018 10:18	1516346290	1.2	6.67	6.39	-12	8.2	16	0.4
34	D1	-1.295813	36.822273	36	1670.3	SE	148	1/19/2018 10:18	1516346298	1.2	10	3.33	-1	0.1	8	0.42
35	D1	-1.296475	36.822666	26	1666.4	SE	150	1/19/2018 10:18	1516346308	1.2	7.22	-2.78	2	-3.9	10	-0.28
36	D1	-1.297395	36.823219	32	1660.6	SE	149	1/19/2018 10:18	1516346322	1	8.89	1.67	-1	-5.8	14	0.12
37	D1	-1.29786	36.823494	39	1662.4	SE	150	1/19/2018 10:18	1516346328	1	10.83	1.94	1	1.8	6	0.32
38	D1	-1.298323	36.823765	42	1663.4	SE	150	1/19/2018 10:18	1516346333	1	11.67	0.84	0	1	5	0.17
39	D1	-1.298753	36.823956	37	1663.8	SE	161	1/19/2018 10:18	1516346338	1	10.28	-1.39	11	0.4	5	-0.28
40	D1	-1.299202	36.82407	25	1664.6	SE	168	1/19/2018 10:19	1516346344	1	6.94	-3.34	7	0.8	6	-0.56
41	D1	-1.299303	36.824085	0	1667.6	SE	165	1/19/2018 10:19	1516346354	1	0	-6.94	-3	3	10	-0.69
42	D1	-1.2993	36.824081	0	1666.9	SE	165	1/19/2018 10:19	1516346364	0.8	0	0	0	-0.7	10	0
43	D1	-1.2993	36.824081	0	1666.9	SE	165	1/19/2018 10:19	1516346374	0.8	0	0	0	0	10	0
44	D1	-1.2993	36.824081	0	1666.9	SE	165	1/19/2018 10:19	1516346384	0.8	0	0	0	0	10	0
45	D1	-1.299307	36.824097	7	1663	SE	169	1/19/2018 10:19	1516346394	0.8	1.94	1.94	4	-3.9	10	0.19
46	D1	-1.299643	36.824242	25	1661.6	SE	140	1/19/2018 10:20	1516346402	0.8	6.94	5	-29	-1.4	8	0.63
47	D1	-1.300125	36.824371	30	1660.1	SE	179	1/19/2018 10:20	1516346410	0.8	8.33	1.39	39	-1.5	8	0.17
48	D1	-1.300463	36.824474	40	1660.3	SE	157	1/19/2018 10:20	1516346414	0.8	11.11	2.78	-22	0.2	4	0.7
49	D1	-1.300983	36.824711	49	1661.1	SE	155	1/19/2018 10:20	1516346419	0.8	13.61	2.5	-2	0.8	5	0.5
50	D1	-1.301447	36.824932	49	1661.2	SE	155	1/19/2018 10:20	1516346423	0.8	13.61	0	0	0.1	4	0
51	D1	-1.30183	36.825108	39	1662.6	SE	155	1/19/2018 10:20	1516346427	0.8	10.83	-2.78	0	1.4	4	-0.7
52	D1	-1.302402	36.825378	20	1661.8	SE	155	1/19/2018 10:20	1516346441	0.8	5.56	-5.27	0	-0.8	14	-0.38
53	D1	-1.302548	36.825447	13	1661.6	SE	157	1/19/2018 10:20	1516346445	0.8	3.61	-1.95	2	-0.2	4	-0.49
54	D1	-1.30269	36.825508	2	1660.8	SE	154	1/19/2018 10:20	1516346454	0.8	0.56	-3.05	-3	-0.8	9	-0.34
55	D1	-1.302808	36.825565	3	1660	SE	157	1/19/2018 10:21	1516346464	0.8	0.83	0.27	3	-0.8	10	0.03
56	D1	-1.302878	36.825596	7	1660.1	SE	156	1/19/2018 10:21	1516346473	0.8	1.94	1.11	-1	0.1	9	0.12
57	D1	-1.303087	36.825691	4	1660.7	SE	154	1/19/2018 10:21	1516346484	0.8	1.11	-0.83	-2	0.6	11	-0.08
58	D1	-1.30335	36.825794	13	1661.5	SE	155	1/19/2018 10:21	1516346503	0.8	3.61	2.5	1	0.8	19	0.13
59	D1	-1.303622	36.825932	8	1661.4	SE	156	1/19/2018 10:21	1516346514	0.8	2.22	-1.39	1	-0.1	11	-0.13
60	D1	-1.303683	36.825958	0	1660.5	SE	159	1/19/2018 10:22	1516346524	0.8	0	-2.22	3	-0.9	10	-0.22
61	D1	-1.303685	36.825958	0	1660.9	SE	159	1/19/2018 10:22	1516346534	0.8	0	0	0	0.4	10	0
62	D1	-1.303688	36.825966	2	1661.2	SE	153	1/19/2018 10:22	1516346544	0.8	0.56	0.56	-6	0.3	10	0.06
63	D1	-1.303695	36.825977	0	1660.1	SE	152	1/19/2018 10:22	1516346554	0.8	0	-0.56	-1	-1.1	10	-0.06
64	D1	-1.3037	36.825981	3	1658.3	SE	156	1/19/2018 10:22	1516346564	0.8	0.83	0.83	4	-1.8	10	0.08
65	D1	-1.3038	36.826023	0	1657.7	SE	155	1/19/2018 10:22	1516346574	0.8	0	-0.83	-1	-0.6	10	-0.08
66	D1	-1.303815	36.826023	0	1657.5	SE	155	1/19/2018 10:23	1516346584	0.8	0	0	0	-0.2	10	0
67	D1	-1.303852	36.826038	7	1657.8	SE	157	1/19/2018 10:23	1516346595	0.8	1.94	1.94	2	0.3	11	0.18
68	D1	-1.303978	36.826092	2	1657.9	SE	156	1/19/2018 10:23	1516346605	0.8	0.56	-1.38	-1	0.1	10	-0.14
69	D1	-1.303985	36.826103	0	1657.4	SE	156	1/19/2018 10:23	1516346615	0.8	0	-0.56	0	-0.5	10	-0.06
70	D1	-1.304208	36.826206	7	1657.5	SE	163	1/19/2018 10:23	1516346625	0.8	1.94	1.94	7	0.1	10	0.19
71	D1	-1.304347	36.826271	3	1656.1	SE	161	1/19/2018 10:23	1516346635	0.8	0.83	-1.11	-2	-1.4	10	-0.11
72	D1	-1.304428	36.826233	4	1663.4	SE	156	1/19/2018 10:24	1516346645	0.8	1.11	0.28	-5	7.3	10	0.03
73	D1	-1.304473	36.826298	0	1663.3	SE	155	1/19/2018 10:24	1516346655	0.8	0	-1.11	-1	-0.1	10	-0.11
74	D1	-1.304473	36.826302	0	1663.4	SE	155	1/19/2018 10:24	1516346665	0.8	0	0	0	0.1	10	0

75	D1	-1.304473	36.826302	0	1663.4	SE	155	1/19/2018 10:24	1516346685	0.8	0	0	0	0	20	0
76	D1	-1.304493	36.826309	0	1661.2	SE	150	1/19/2018 10:24	1516346695	0.8	0	0	-5	-2.2	10	0
77	D1	-1.304493	36.826309	0	1661.2	SE	150	1/19/2018 10:25	1516346705	0.8	0	0	0	0	10	0
78	D1	-1.304533	36.826347	10	1660.2	SE	134	1/19/2018 10:25	1516346715	0.8	2.78	2.78	-16	-1	10	0.28
79	D1	-1.304633	36.826481	19	1660.2	SE	125	1/19/2018 10:25	1516346719	0.8	5.28	2.5	-9	0	4	0.63
80	D1	-1.304752	36.826611	9	1660.2	SE	141	1/19/2018 10:25	1516346723	0.8	2.5	-2.78	16	0	4	-0.7
81	D1	-1.304802	36.826649	5	1659.7	SE	156	1/19/2018 10:25	1516346727	0.8	1.39	-1.11	15	-0.5	4	-0.28
82	D1	-1.305202	36.826263	27	1658	SW	258	1/19/2018 10:25	1516346741	0.8	7.5	6.11	102	-1.7	14	0.44
83	D1	-1.305298	36.825962	34	1657.9	SW	250	1/19/2018 10:25	1516346745	0.8	9.44	1.94	-8	-0.1	4	0.49
84	D1	-1.30541	36.825626	33	1658	SW	255	1/19/2018 10:25	1516346749	0.8	9.17	-0.27	5	0.1	4	-0.07
85	D1	-1.305487	36.825279	20	1659	SW	261	1/19/2018 10:25	1516346755	0.8	5.56	-3.61	6	1	6	-0.6
86	D1	-1.305508	36.825096	20	1659.3	SW	263	1/19/2018 10:25	1516346759	0.8	5.56	0	2	0.3	4	0
87	D1	-1.305562	36.824684	33	1660.5	SW	262	1/19/2018 10:26	1516346765	0.8	9.17	3.61	-1	1.2	6	0.6
88	D1	-1.305612	36.824341	35	1660.8	SW	262	1/19/2018 10:26	1516346769	0.8	9.72	0.55	0	0.3	4	0.14
89	D1	-1.305675	36.82386	41	1662.8	SW	263	1/19/2018 10:26	1516346774	0.9	11.39	1.67	1	2	5	0.33
90	D1	-1.305755	36.823288	48	1663.8	SW	262	1/19/2018 10:26	1516346779	0.8	13.33	1.94	-1	1	5	0.39
91	D1	-1.305832	36.8228	50	1664	SW	261	1/19/2018 10:26	1516346783	0.8	13.89	0.56	-1	0.2	4	0.14
92	D1	-1.306437	36.820675	47	1664.6	SW	252	1/19/2018 10:26	1516346801	0.8	13.06	-0.83	-9	0.6	18	-0.05
93	D1	-1.306627	36.820263	46	1664.6	SW	241	1/19/2018 10:26	1516346805	0.8	12.78	-0.28	-11	0	4	-0.07
94	D1	-1.306943	36.81992	34	1665.5	SW	209	1/19/2018 10:26	1516346810	0.8	9.44	-3.34	-32	0.9	5	-0.67
95	D1	-1.307388	36.819599	25	1666.5	SW	238	1/19/2018 10:26	1516346819	0.8	6.94	-2.5	29	1	9	-0.28
96	D1	-1.307755	36.819389	34	1666.6	SW	205	1/19/2018 10:27	1516346825	0.8	9.44	2.5	-33	0.1	6	0.42
97	D1	-1.308095	36.819252	34	1666.6	SW	205	1/19/2018 10:27	1516346829	0.8	9.44	0	0	0	4	0
98	D1	-1.308602	36.819042	40	1666.5	SW	203	1/19/2018 10:27	1516346835	0.8	11.11	1.67	-2	-0.1	6	0.28
99	D1	-1.30909	36.81876	48	1666.2	SW	214	1/19/2018 10:27	1516346840	0.8	13.33	2.22	11	-0.3	5	0.44
100	D1	-1.309515	36.818451	54	1666	SW	217	1/19/2018 10:27	1516346844	0.8	15	1.67	3	-0.2	4	0.42
101	D1	-1.309972	36.818092	60	1665	SW	217	1/19/2018 10:27	1516346848	0.8	16.67	1.67	0	-1	4	0.42
102	D1	-1.311733	36.816715	59	1663.9	SW	218	1/19/2018 10:27	1516346862	0.8	16.39	-0.28	1	-1.1	14	-0.02
103	D1	-1.312185	36.816372	57	1664.1	SW	218	1/19/2018 10:27	1516346866	0.8	15.83	-0.56	0	0.2	4	-0.14
104	D1	-1.312577	36.816067	24	1665.6	SW	202	1/19/2018 10:27	1516346872	0.8	6.67	-9.16	-16	1.5	6	-1.53
105	D1	-1.312715	36.816044	7	1665.7	SW	194	1/19/2018 10:27	1516346876	0.8	1.94	-4.73	-8	0.1	4	-1.18
106	D1	-1.313008	36.815845	30	1668	SW	214	1/19/2018 10:28	1516346884	0.8	8.33	6.39	20	2.3	8	0.8
107	D1	-1.313427	36.815636	41	1668.9	SW	206	1/19/2018 10:28	1516346889	0.8	11.39	3.06	-8	0.9	5	0.61
108	D1	-1.313833	36.815441	46	1669.2	SW	207	1/19/2018 10:28	1516346893	0.8	12.78	1.39	1	0.3	4	0.35
109	D1	-1.314725	36.815002	49	1673.2	SW	207	1/19/2018 10:28	1516346901	0.8	13.61	0.83	0	4	8	0.1
110	D1	-1.315182	36.814762	52	1676	SW	210	1/19/2018 10:28	1516346905	0.8	14.44	0.83	3	2.8	4	0.21
111	D1	-1.315617	36.814453	54	1678.1	SW	219	1/19/2018 10:28	1516346909	0.8	15	0.56	9	2.1	4	0.14
112	D1	-1.316932	36.813156	46	1682	SW	223	1/19/2018 10:28	1516346923	0.8	12.78	-2.22	4	3.9	14	-0.16
113	D1	-1.317273	36.812813	50	1682.1	SW	226	1/19/2018 10:28	1516346927	0.8	13.89	1.11	3	0.1	4	0.28
114	D1	-1.31763	36.812443	53	1683	SW	227	1/19/2018 10:28	1516346931	0.8	14.72	0.83	1	0.9	4	0.21
115	D1	-1.318002	36.812038	57	1684.1	SW	228	1/19/2018 10:28	1516346935	0.8	15.83	1.11	1	1.1	4	0.28
116	D1	-1.318402	36.811607	60	1685.2	SW	226	1/19/2018 10:28	1516346939	0.8	16.67	0.84	-2	1.1	4	0.21
117	D1	-1.31885	36.811161	65	1686.2	SW	225	1/19/2018 10:29	1516346943	0.8	18.06	1.39	-1	1	4	0.35
118	D1	-1.31933	36.810692	69	1686.9	SW	224	1/19/2018 10:29	1516346947	0.8	19.17	1.11	-1	0.7	4	0.28
119	D1	-1.320382	36.809662	76	1687.6	SW	225	1/19/2018 10:29	1516346955	0.8	21.11	1.94	1	0.7	8	0.24
120	D1	-1.320938	36.809109	79	1688	SW	225	1/19/2018 10:29	1516346959	0.8	21.94	0.83	0	0.4	4	0.21
121	D1	-1.321987	36.807968	73	1689.8	SW	237	1/19/2018 10:29	1516346967	0.8	20.28	-1.66	12	1.8	8	-0.21
122	D1	-1.322815	36.804523	56	1690.3	SW	262	1/19/2018 10:29	1516346989	0.8	15.56	-4.72	25	0.5	22	-0.21
123	D1	-1.322885	36.803993	53	1691.4	SW	262	1/19/2018 10:29	1516346993	0.8	14.72	-0.84	0	1.1	4	-0.21
124	D1	-1.322962	36.803493	50	1692.4	SW	261	1/19/2018 10:29	1516346997	0.8	13.89	-0.83	-1	1	4	-0.21
125	D1	-1.323037	36.80302	49	1692.6	SW	260	1/19/2018 10:30	1516347001	0.8	13.61	-0.28	-1	0.2	4	-0.07
126	D1	-1.323125	36.802536	49	1692.8	SW	260	1/19/2018 10:30	1516347005	0.8	13.61	0	0	0.2	4	0
127	D1	-1.323222	36.802059	49	1692.8	SW	259	1/19/2018 10:30	1516347009	0.8	13.61	0	-1	0	4	0
128	D1	-1.323315	36.801567	51	1693	SW	258	1/19/2018 10:30	1516347013	0.8	14.17	0.56	-1	0.2	4	0.14
129	D1	-1.323432	36.801071	50	1693.2	SW	257	1/19/2018 10:30	1516347017	0.8	13.89	-0.28	-1	0.2	4	-0.07
130	D1	-1.323537	36.800575	51	1693.9	SW	259	1/19/2018 10:30	1516347021	0.8	14.17	0.28	2	0.7	4	0.07
131	D1	-1.323622	36.800091	50	1694.6	SW	260	1/19/2018 10:30	1516347025	0.8	13.89	-0.28	1	0.7	4	-0.07
132	D1	-1.323715	36.799622	48	1695	SW	258	1/19/2018 10:30	1516347029	0.8	13.33	-0.56	-2	0.4	4	-0.14
133	D1	-1.324033	36.798061	45	1699.3	SW	259	1/19/2018 10:30	1516347043	0.8	12.5	-0.83	1	4.3	14	-0.06
134	D1	-1.32415	36.797531	44	1701.8	SW	258	1/19/2018 10:30	1516347048	0.8	12.22	-0.28	-1	2.5	5	-0.06
135	D1	-1.324295	36.797009	44	1704	SW	251	1/19/2018 10:30	1516347053	0.8	12.22	0	-7	2.2	5	0
136	D1	-1.324523	36.796497	45	1706.1	SW	243	1/19/2018 10:30	1516347058	0.8	12.5	0.28	-8	2.1	5	0.06
137	D1	-1.324752	36.796097	47	1706.4	SW	241	1/19/2018 10:31	1516347062	0.8	13.06	0.56	-2	0.3	4	0.14
138	D1	-1.324992	36.795689	47	1708	SW	240	1/19/2018 10:31	1516347066	0.8	13.06	0	-1	1.6	4	0
139	D1	-1.325457	36.794888	45	1712.7	SW	240	1/19/2018 10:31	1516347074	0.8	12.5	-0.56	0	4.7	8	-0.07
140	D1	-1.326243	36.79353	47	1721.2	SW	241	1/19/2018 10:31	1516347088	0.8	13.06	0.56	1	8.5	14	0.04
141	D1	-1.327055	36.792103	47	1727.4	SW	240	1/19/2018 10:31	1516347102	0.8	13.06	0	-1	6.2	14	0
142	D1	-1.328035	36.790432	49	1735.7	SW	238	1/19/2018 10:31	1516347118	0.8	13.61	0.55	-2	8.3	16	0.03
143	D1	-1.328292	36.790016	49	1738.4	SW	240	1/19/2018 10:32	1516347122	0.8	13.61	0	2	2.7	4	0
144	D1	-1.328532	36.789597	49	1740.8	SW	240	1/19/2018 10:32	1516347126	0.8	13.61	0	0	2.4	4	0
145	D1	-1.328772	36.789165	50	1742.3	SW	241	1/19/2018 10:32	1516347130	0.8	13.89	0.28	1	1.5	4	0.07
146	D1	-1.329005	36.788715	51	1743.4	SW	243	1/19/2018 10:32	1516347134	0.8	14.17	0.28	2	1.1	4	0.07
147	D1	-1.329232	36.788265	50	1744.1	SW	242	1/19/2018 10:32	1516347138	0.8	13.89	-0.28	-1	0.7	4	-0.07
148	D1	-1.329468	36.78783	50	1744.9	SW	241	1/19/2018 10:32	1516347142	0.8	13.89	0	-1	0.8	4	0
149	D1	-1.329717	36.787384	51	1745.7	SW	241	1/19/2018 10:32	1516347146	0.8	14.17	0.28	0	0.8	4	0.07
150	D1	-1.331545	36.784103	64	1750.3	SW	241	1/19/2018 10:32	1516347172	0.8	17.78	3.61	0	4.6	26	0.14
151	D1	-1.331847	36.783569	61	1752	SW	241	1/19/2018 10:32	1516347176	0.8	16.94	-0.84	0	1.7	4	-0.21
152	D1	-1.332133	36.783058	57	1754.6	SW	241	1/19/2018 10:33	1516347180	0.8	15.83	-1.11	0	2.6	4	-0.28
153	D1	-1.332415	36.782581	56	1757.1	SW	240	1/19/2018 10:33	1516347184	0.8	15.56	-0.27	-1	2.5	4	-0.07
154	D1	-1.33272	36.782104	56	1759.8	SW	236	1/19/2018 10:33	1516347188	0.8	15.56	0	-4	2.7	4	0
155	D1	-1.333038	36.781635	56	1761.8	SW	238	1/19/2018 10:33	1516347192	0.8	15.56	0	2	2	4	0
156	D1	-1.333305	36.781162	55	1763.6	SW	241	1/19/2018 10:33	1516347196	0.8	15.28	-0.28	3	1.8	4	-0.07
157	D1	-1.333563	36.780685	54	1765.2	SW	242	1/19/2018 10:33	1516347200	0.8	15	-0.28	1	1.6	4	-0.07
158	D1	-1.33412	36.779743	55	1769.4	SW	238	1/19/2018 10:33	1516347208	0.8	15.28	0.28	-4	4.2	8	0.03

159	D1	-1.334712	36.778561	6	1776	SW	242	1/19/2018 10:33	1516347222	0.8	1.67	-13.61	4	6.6	14	-0.97
160	D1	-1.334733	36.778511	10	1776	SW	244	1/19/2018 10:33	1516347226	0.8	2.78	1.11	2	0	4	0.28
161	D1	-1.334967	36.778091	36	1777.9	SW	240	1/19/2018 10:33	1516347235	0.8	10	7.22	-4	1.9	9	0.8
162	D1	-1.33521	36.77766	43	1779	SW	242	1/19/2018 10:34	1516347240	0.8	11.94	1.94	2	1.1	5	0.39
163	D1	-1.33543	36.777267	46	1779.3	SW	241	1/19/2018 10:34	1516347244	0.8	12.78	0.84	-1	0.3	4	0.21
164	D1	-1.335688	36.77684	53	1780.4	SW	239	1/19/2018 10:34	1516347248	0.8	14.72	1.94	-2	1.1	4	0.49
165	D1	-1.33599	36.77636	59	1781	SW	238	1/19/2018 10:34	1516347252	0.8	16.39	1.67	-1	0.6	4	0.42
166	D1	-1.33634	36.775829	66	1780.4	SW	234	1/19/2018 10:34	1516347256	0.8	18.33	1.94	-4	-0.6	4	0.48
167	D1	-1.336788	36.775272	74	1778.6	SW	230	1/19/2018 10:34	1516347260	0.8	20.56	2.23	-4	-1.8	4	0.56
168	D1	-1.337248	36.774704	72	1776.6	SW	232	1/19/2018 10:34	1516347264	0.8	20	-0.56	2	-2	4	-0.14
169	D1	-1.337675	36.774166	64	1774.7	SW	232	1/19/2018 10:34	1516347268	0.8	17.78	-2.22	0	-1.9	4	-0.56
170	D1	-1.338685	36.772861	53	1778	SW	232	1/19/2018 10:34	1516347282	0.8	14.72	-3.06	0	3.3	14	-0.22
171	D1	-1.339023	36.77243	55	1778.8	SW	233	1/19/2018 10:34	1516347286	0.8	15.28	0.56	1	0.8	4	0.14
172	D1	-1.339387	36.771961	60	1782	SW	232	1/19/2018 10:34	1516347290	0.8	16.67	1.39	-1	3.2	4	0.35
173	D1	-1.339773	36.771484	62	1784.5	SW	231	1/19/2018 10:34	1516347294	0.8	17.22	0.55	-1	2.5	4	0.14
174	D1	-1.340167	36.770992	64	1786.7	SW	232	1/19/2018 10:34	1516347298	0.8	17.78	0.56	1	2.2	4	0.14
175	D1	-1.34056	36.770489	59	1788.5	SW	232	1/19/2018 10:35	1516347302	0.8	16.39	-1.39	0	1.8	4	-0.35
176	D1	-1.340742	36.770271	25	1789.3	SW	232	1/19/2018 10:35	1516347306	0.8	6.94	-9.45	0	0.8	4	-2.36
177	D1	-1.340935	36.770035	37	1789	SW	230	1/19/2018 10:35	1516347310	0.8	10.28	3.34	-2	-0.3	4	0.84
178	D1	-1.341275	36.7696	50	1789	SW	232	1/19/2018 10:35	1516347315	0.8	13.89	3.61	2	0	5	0.72
179	D1	-1.341608	36.769169	56	1789.1	SW	234	1/19/2018 10:35	1516347319	0.8	15.56	1.67	2	0.1	4	0.42
180	D1	-1.341947	36.768677	60	1789.6	SW	237	1/19/2018 10:35	1516347323	0.8	16.67	1.11	3	0.5	4	0.28
181	D1	-1.342228	36.768131	61	1790.8	SW	245	1/19/2018 10:35	1516347327	0.8	16.94	0.27	8	1.2	4	0.07
182	D1	-1.343518	36.766518	66	1798	SW	200	1/19/2018 10:35	1516347341	0.8	18.33	1.39	-45	7.2	14	0.1
183	D1	-1.344187	36.766304	70	1798.1	SW	198	1/19/2018 10:35	1516347345	0.8	19.44	1.11	-2	0.1	4	0.28
184	D1	-1.344855	36.766102	69	1798.2	SW	198	1/19/2018 10:35	1516347349	0.8	19.17	-0.27	0	0.1	4	-0.07
185	D1	-1.345458	36.765839	64	1798.2	SW	206	1/19/2018 10:35	1516347353	0.8	17.78	-1.39	8	0	4	-0.35
186	D1	-1.34591	36.765663	40	1798	SW	200	1/19/2018 10:35	1516347357	0.8	11.11	-6.67	-6	-0.2	4	-1.67
187	D1	-1.346368	36.765503	33	1796.6	SW	200	1/19/2018 10:36	1516347365	0.8	9.17	-1.94	0	-1.4	8	-0.24
188	D1	-1.346847	36.765339	45	1795.9	SW	199	1/19/2018 10:36	1516347370	0.8	12.5	3.33	-1	-0.7	5	0.67
189	D1	-1.347313	36.765171	51	1795.7	SW	200	1/19/2018 10:36	1516347374	0.8	14.17	1.67	1	-0.2	4	0.42
190	D1	-1.347827	36.764988	56	1795.1	SW	199	1/19/2018 10:36	1516347378	0.8	15.56	1.39	-1	-0.6	4	0.35
191	D1	-1.349707	36.764198	68	1789.2	SW	216	1/19/2018 10:36	1516347390	0.9	18.89	3.33	17	-5.9	12	0.28
192	D1	-1.350967	36.763306	39	1795.4	SW	214	1/19/2018 10:36	1516347404	0.8	10.83	-8.06	-2	6.2	14	-0.58
193	D1	-1.351378	36.763103	35	1795.9	SW	201	1/19/2018 10:36	1516347409	0.8	9.72	-1.11	-13	0.5	5	-0.22
194	D1	-1.351862	36.762974	34	1794.6	SW	195	1/19/2018 10:36	1516347415	0.8	9.44	-0.28	-6	-1.3	6	-0.05
195	D1	-1.35237	36.762875	27	1793.9	SW	194	1/19/2018 10:37	1516347424	0.8	7.5	-1.94	-1	-0.7	9	-0.22
196	D1	-1.352855	36.762733	48	1791.8	SW	203	1/19/2018 10:37	1516347429	0.8	13.33	5.83	9	-2.1	5	1.17
197	D1	-1.353355	36.762489	57	1790.8	SW	205	1/19/2018 10:37	1516347433	0.8	15.83	2.5	2	-1	4	0.63
198	D1	-1.353895	36.762238	58	1786.2	SW	205	1/19/2018 10:37	1516347437	0.8	16.11	0.28	0	-4.6	4	0.07
199	D1	-1.354415	36.762009	54	1784.5	SW	203	1/19/2018 10:37	1516347441	0.8	15	-1.11	-2	-1.7	4	-0.28
200	D1	-1.354888	36.761883	47	1787.2	SW	187	1/19/2018 10:37	1516347445	0.8	13.06	-1.94	-16	2.7	4	-0.49
201	D1	-1.355317	36.761925	43	1791.5	SE	170	1/19/2018 10:37	1516347449	0.8	11.94	-1.12	-17	4.3	4	-0.28
202	D1	-1.356217	36.762161	35	1795.4	SE	167	1/19/2018 10:37	1516347463	0.8	9.72	-2.22	-3	3.9	14	-0.16
203	D1	-1.35653	36.762241	30	1794.9	SE	164	1/19/2018 10:37	1516347467	0.8	8.33	-1.39	-3	-0.5	4	-0.35
204	D1	-1.356695	36.762291	15	1793.3	SE	166	1/19/2018 10:37	1516347471	0.8	4.17	-4.16	2	-1.6	4	-1.04
205	D1	-1.356927	36.762356	22	1791.8	SE	166	1/19/2018 10:37	1516347476	0.8	6.11	1.94	0	-1.5	5	0.39
206	D1	-1.357243	36.762428	29	1791.5	SE	167	1/19/2018 10:38	1516347481	0.8	8.06	1.95	1	-0.3	5	0.39
207	D1	-1.357655	36.762527	36	1791.3	SE	166	1/19/2018 10:38	1516347486	0.8	10	1.94	-1	-0.2	5	0.39
208	D1	-1.358127	36.762611	39	1792.3	SE	173	1/19/2018 10:38	1516347491	0.8	10.83	0.83	7	1	5	0.17
209	D1	-1.358643	36.762634	42	1793.1	SE	177	1/19/2018 10:38	1516347496	0.8	11.67	0.84	4	0.8	5	0.17
210	D1	-1.359183	36.762669	43	1793.6	SE	176	1/19/2018 10:38	1516347501	0.8	11.94	0.27	-1	0.5	5	0.05
211	D1	-1.359732	36.762695	45	1794.1	SE	176	1/19/2018 10:38	1516347506	0.8	12.5	0.56	0	0.5	5	0.11
212	D1	-1.36019	36.762733	45	1794.2	SE	175	1/19/2018 10:38	1516347510	0.8	12.5	0	-1	0.1	4	0
213	D1	-1.361612	36.763557	52	1792.1	SE	138	1/19/2018 10:38	1516347524	0.8	14.44	1.94	-37	-2.1	14	0.14
214	D1	-1.36202	36.763924	55	1791.7	SE	138	1/19/2018 10:38	1516347528	0.8	15.28	0.84	0	-0.4	4	0.21
215	D1	-1.362438	36.764301	55	1789.5	SE	139	1/19/2018 10:38	1516347532	0.8	15.28	0	1	-2.2	4	0
216	D1	-1.362847	36.764675	55	1788	SE	138	1/19/2018 10:38	1516347536	0.8	15.28	0	-1	-1.5	4	0
217	D1	-1.36325	36.765038	53	1786.8	SE	138	1/19/2018 10:39	1516347540	0.8	14.72	-0.56	0	-1.2	4	-0.14
218	D1	-1.363622	36.765373	50	1785.5	SE	137	1/19/2018 10:39	1516347544	0.8	13.89	-0.83	-1	-1.3	4	-0.21
219	D1	-1.364017	36.765713	36	1783.2	SE	140	1/19/2018 10:39	1516347549	0.8	10	-3.89	3	-2.3	5	-0.78
220	D1	-1.364267	36.765911	12	1780.6	SE	150	1/19/2018 10:39	1516347557	0.8	3.33	-6.67	10	-2.6	8	-0.83
221	D1	-1.364432	36.765999	17	1778.7	SE	145	1/19/2018 10:39	1516347562	0.8	4.72	1.39	-5	-1.9	5	0.28
222	D1	-1.364758	36.766209	39	1776.5	SE	150	1/19/2018 10:39	1516347567	0.8	10.83	6.11	5	-2.2	5	1.22
223	D1	-1.365772	36.766762	27	1775	SE	150	1/19/2018 10:39	1516347581	0.8	7.5	-3.33	0	-1.5	14	-0.24
224	D1	-1.366062	36.766918	16	1776.8	SE	151	1/19/2018 10:39	1516347587	0.8	4.44	-3.06	1	1.8	6	-0.51
225	D1	-1.366207	36.766987	11	1778.4	SE	152	1/19/2018 10:39	1516347594	0.8	3.06	-1.38	1	1.6	7	-0.2
226	D1	-1.366633	36.767223	25	1779.2	SE	151	1/19/2018 10:40	1516347603	0.8	6.94	3.88	-1	0.8	9	0.43
227	D1	-1.36686	36.767353	28	1779.2	SE	151	1/19/2018 10:40	1516347607	0.8	7.78	0.84	0	0	4	0.21
228	D1	-1.367135	36.767498	34	1779	SE	153	1/19/2018 10:40	1516347611	0.8	9.44	1.66	2	-0.2	4	0.42
229	D1	-1.367578	36.767662	40	1777.4	SE	166	1/19/2018 10:40	1516347616	0.8	11.11	1.67	13	-1.6	5	0.33
230	D1	-1.368127	36.7677	44	1778.9	SW	184	1/19/2018 10:40	1516347621	0.8	12.22	1.11	18	1.5	5	0.22
231	D1	-1.36867	36.767609	43	1781	SW	191	1/19/2018 10:40	1516347626	0.8	11.94	-0.28	7	2.1	5	-0.06
232	D1	-1.369092	36.767517	44	1781.3	SW	190	1/19/2018 10:40	1516347630	0.8	12.22	0.28	-1	0.3	4	0.07
233	D1	-1.370623	36.76786	51	1779.2	SE	153	1/19/2018 10:40	1516347644	0.8	14.17	1.95	-37	-2.1	14	0.14
234	D1	-1.37161	36.768356	52	1776.7	SE	153	1/19/2018 10:40	1516347652	0.8	14.44	0.27	0	-2.5	8	0.03
235	D1	-1.372058	36.768589	50	1774	SE	154	1/19/2018 10:40	1516347656	0.8	13.89	-0.55	1	-2.7	4	-0.14
236	D1	-1.372503	36.768814	50	1771.5	SE	153	1/19/2018 10:41	1516347660	0.8	13.89	0	-1	-2.5	4	0
237	D1	-1.372965	36.769035	53	1769.4	SE	155	1/19/2018 10:41	1516347664	0.8	14.72	0.83	2	-2.1	4	0.21
238	D1	-1.373443	36.769238	51	1767.2	SE	159	1/19/2018 10:41	1516347668	0.8	14.17	-0.55	4	-2.2	4	-0.14
239	D1	-1.373928	36.769402	50	1765.9	SE	163	1/19/2018 10:41	1516347672	0.8	13.89	-0.28	4	-1.3	4	-0.07
240	D1	-1.374387	36.769531	46	1765.8	SE	166	1/19/2018 10:41	1516347676	0.8	12.78	-1.11	3	-0.1	4	-0.28
241	D1	-1.374832	36.769619	45	1766.6	SE	170	1/19/2018 10:41	1516347680	0.8	12.5	-0.28	4	0.8	4	-0.07
242	D1	-1.37532	36.769684	36	1767.8	SE	171	1/19/2018 10:41	1516347685	0.8	10	-2.5	1	1.2	5	-0.5

243	D1	-1.375638	36.769714	31	1767.6	SE	172	1/19/2018 10:41	1516347689	0.8	8.61	-1.39	1	-0.2	4	-0.35
244	D1	-1.376472	36.769825	22	1761.6	SE	173	1/19/2018 10:41	1516347703	0.8	6.11	-2.5	1	-6	14	-0.18
245	D1	-1.376702	36.769852	23	1761.2	SE	171	1/19/2018 10:41	1516347707	0.8	6.39	0.28	-2	-0.4	4	0.07
246	D1	-1.37697	36.769897	21	1757.3	SE	171	1/19/2018 10:41	1516347712	0.8	5.83	-0.56	0	-3.9	5	-0.11
247	D1	-1.377277	36.769943	27	1754.9	SE	172	1/19/2018 10:41	1516347717	0.8	7.5	1.67	1	-2.4	5	0.33
248	D1	-1.37756	36.769985	30	1754.4	SE	172	1/19/2018 10:42	1516347721	0.8	8.33	0.83	0	-0.5	4	0.21
249	D1	-1.378063	36.770061	34	1746.4	SE	172	1/19/2018 10:42	1516347727	0.8	9.44	1.11	0	-8	6	0.19
250	D1	-1.37861	36.770149	40	1740.4	SE	173	1/19/2018 10:42	1516347733	0.8	11.11	1.67	1	-6	6	0.28
251	D1	-1.379003	36.770206	39	1739.4	SE	171	1/19/2018 10:42	1516347737	0.8	10.83	-0.28	-2	-1	4	-0.07
252	D1	-1.379403	36.770264	40	1735.1	SE	172	1/19/2018 10:42	1516347741	0.8	11.11	0.28	1	-4.3	4	0.07
253	D1	-1.379863	36.770325	33	1730.2	SE	172	1/19/2018 10:42	1516347746	0.8	9.17	-1.94	0	-4.9	5	-0.39
254	D1	-1.380172	36.770363	31	1730.1	SE	172	1/19/2018 10:42	1516347750	0.8	8.61	-0.56	0	-0.1	4	-0.14
255	D1	-1.380833	36.770451	12	1728.9	SE	169	1/19/2018 10:42	1516347764	0.8	3.33	-5.28	-3	-1.2	14	-0.38
256	D1	-1.381333	36.770523	28	1728.1	SE	173	1/19/2018 10:42	1516347774	0.8	7.78	4.45	4	-0.8	10	0.45
257	D1	-1.381622	36.770554	29	1727.9	SE	172	1/19/2018 10:42	1516347778	0.8	8.06	0.28	-1	-0.2	4	0.07
258	D1	-1.381903	36.770592	27	1727.2	SE	172	1/19/2018 10:43	1516347782	0.8	7.5	-0.56	0	-0.7	4	-0.14
259	D1	-1.382058	36.770481	21	1726.5	SW	257	1/19/2018 10:43	1516347786	0.8	5.83	-1.67	85	-0.7	4	-0.42
260	D1	-1.382078	36.770191	6	1727.2	SW	262	1/19/2018 10:43	1516347794	0.8	1.67	-4.16	5	0.7	8	-0.52
261	D1	-1.382075	36.770161	0	1727.3	SW	262	1/19/2018 10:43	1516347798	0.8	0	-1.67	0	0.1	4	-0.42
262	D1	-1.382072	36.770168	0	1726.4	SW	262	1/19/2018 10:43	1516347807	0.8	0	0	0	-0.9	9	0
263	D1	-1.382097	36.76989	19	1728.8	W	270	1/19/2018 10:43	1516347827	0.8	5.28	5.28	8	2.4	20	0.26
264	D1	-1.382087	36.769676	22	1728.9	NW	276	1/19/2018 10:43	1516347831	0.8	6.11	0.83	6	0.1	4	0.21
265	D1	-1.382077	36.769386	17	1729.5	SW	269	1/19/2018 10:43	1516347837	0.8	4.72	-1.39	-7	0.6	6	-0.23
266	D1	-1.382068	36.769161	17	1730.1	W	270	1/19/2018 10:44	1516347842	0.8	4.72	0	1	0.6	5	0
267	D1	-1.382073	36.768944	20	1730.9	NW	272	1/19/2018 10:44	1516347847	0.8	5.56	0.84	2	0.8	5	0.17
268	D1	-1.381895	36.7687	27	1730.4	NW	335	1/19/2018 10:44	1516347852	0.8	7.5	1.94	63	-0.5	5	0.39
269	D1	-1.381487	36.76862	33	1729.3	NW	351	1/19/2018 10:44	1516347857	0.8	9.17	1.67	16	-1.1	5	0.33
270	D1	-1.38111	36.768574	27	1729.4	NW	353	1/19/2018 10:44	1516347862	0.8	7.5	-1.67	2	0.1	5	-0.33
271	D1	-1.38075	36.768528	28	1730	NW	355	1/19/2018 10:44	1516347867	0.8	7.78	0.28	2	0.6	5	0.06
272	D1	-1.3802	36.768265	20	1732.1	SW	262	1/19/2018 10:44	1516347881	0.8	5.56	-2.22	-93	2.1	14	-0.16
273	D1	-1.380243	36.767921	21	1732.9	SW	264	1/19/2018 10:44	1516347887	0.8	5.83	0.27	2	0.8	6	0.05
274	D1	-1.380183	36.767792	12	1733.9	NW	328	1/19/2018 10:44	1516347892	0.8	3.33	-2.5	64	1	5	-0.5
275	D1	-1.380085	36.767704	8	1735.9	NW	281	1/19/2018 10:44	1516347897	0.8	2.22	-1.11	-47	2	5	-0.22
276	D1	-1.380038	36.767651	4	1736.3	NW	355	1/19/2018 10:45	1516347901	0.8	1.11	-1.11	74	0.4	4	-0.28
277	D1	-1.380028	36.767647	0	1739.2	NW	351	1/19/2018 10:45	1516347907	0.8	0	-1.11	-4	2.9	6	-0.19

Table 0.3. Sample Data for a Test Segment in Figure 4.7 (Prestudy)

Data Point	Driver	Lat	Lon	Spd (km/h)	Alt	Dir	Dir (°)	Time	GPSTime	GPS Signal Strength	Spd (m/s)	ΔSpd (m/s²)	ΔDir (°)	ΔAlt (m)	ΔTm (s)	Accel/ Decel (m/s²)
1	D1	-1.39172	36.77652	0	1712.4	SE	175	5/21/2018 7:40	1526874051	0.8	0					
2	D1	-1.39169	36.77646	2	1709.5	W	270	5/21/2018 7:42	1526874175	0.9	0.56	0.56	95	-2.9	124	0
3	D1	-1.39166	36.77642	2	1709.1	NW	334	5/21/2018 7:43	1526874182	0.8	0.56	0	64	-0.4	7	0
4	D1	-1.39166	36.77642	5	1707.6	SW	192	5/21/2018 7:43	1526874197	0.8	1.39	0.83	-142	-1.5	15	0.06
5	D1	-1.39185	36.77636	9	1713.1	SW	262	5/21/2018 7:44	1526874253	0.8	2.5	1.11	70	5.5	56	0.02
6	D1	-1.39183	36.77627	21	1713.2	NW	294	5/21/2018 7:44	1526874255	0.8	5.83	3.33	32	0.1	2	1.67
7	D1	-1.39159	36.77582	38	1715.6	NW	300	5/21/2018 7:44	1526874261	0.8	10.56	4.73	6	2.4	6	0.79
8	D1	-1.39134	36.77536	39	1717.4	NW	298	5/21/2018 7:44	1526874266	0.8	10.83	0.27	-2	1.8	5	0.05
9	D1	-1.39114	36.77485	36	1718.7	NW	285	5/21/2018 7:44	1526874272	0.8	10	-0.83	-13	1.3	6	-0.14
10	D1	-1.39108	36.77434	31	1716.7	NW	276	5/21/2018 7:44	1526874278	0.8	8.61	-1.39	-9	-2	6	-0.23
11	D1	-1.39107	36.77336	14	1713	SW	269	5/21/2018 7:44	1526874294	0.8	3.89	-4.72	-7	-3.7	16	-0.3
12	D1	-1.39105	36.77284	36	1719.2	SW	268	5/21/2018 7:45	1526874302	0.8	10	6.11	-1	6.2	8	0.76
13	D1	-1.39102	36.77235	38	1720.9	NW	274	5/21/2018 7:45	1526874307	0.8	10.56	0.56	6	1.7	5	0.11
14	D1	-1.39098	36.77188	35	1720.3	NW	275	5/21/2018 7:45	1526874312	0.8	9.72	-0.84	1	-0.6	5	-0.17
15	D1	-1.39091	36.77134	36	1718.7	NW	277	5/21/2018 7:45	1526874318	0.8	10	0.28	2	-1.6	6	0.05
16	D1	-1.39086	36.77082	34	1718.9	NW	277	5/21/2018 7:45	1526874324	0.8	9.44	-0.56	0	0.2	6	-0.09
17	D1	-1.3908	36.77033	28	1722.5	NW	277	5/21/2018 7:45	1526874331	0.8	7.78	-1.66	0	3.6	7	-0.24
18	D1	-1.39076	36.76985	24	1722.6	NW	272	5/21/2018 7:45	1526874339	0.8	6.67	-1.11	-5	0.1	8	-0.14
19	D1	-1.3908	36.76861	32	1718.5	SW	264	5/21/2018 7:45	1526874354	0.8	8.89	2.22	-8	-4.1	15	0.15
20	D1	-1.39084	36.7681	19	1718	SW	267	5/21/2018 7:46	1526874364	0.8	5.28	-3.61	3	-0.5	10	-0.36
21	D1	-1.39083	36.76761	20	1716.7	NW	277	5/21/2018 7:46	1526874374	0.8	5.56	0.28	10	-1.3	10	0.03
22	D1	-1.39052	36.76697	11	1716.6	NW	346	5/21/2018 7:46	1526874414	0.9	3.06	-2.5	69	-0.1	40	-0.06
23	D1	-1.39043	36.76699	21	1716.7	NE	25	5/21/2018 7:46	1526874416	0.7	5.83	2.77	-321	0.1	2	1.39
24	D1	-1.39009	36.76726	41	1713.4	NE	39	5/21/2018 7:47	1526874421	0.8	11.39	5.56	14	-3.3	5	1.11
25	D1	-1.38966	36.76762	45	1708.8	NE	43	5/21/2018 7:47	1526874426	0.8	12.5	1.11	4	-4.6	5	0.22
26	D1	-1.38934	36.76796	46	1705.6	NE	51	5/21/2018 7:47	1526874430	0.8	12.78	0.28	8	-3.2	4	0.07
27	D1	-1.38909	36.76836	30	1702.8	NE	66	5/21/2018 7:47	1526874435	0.8	8.33	-4.45	15	-2.8	5	-0.89
28	D1	-1.38906	36.76844	3	1701.5	NE	70	5/21/2018 7:47	1526874439	0.7	0.83	-7.5	4	-1.3	4	-1.88
29	D1	-1.3889	36.76888	29	1702.8	NE	69	5/21/2018 7:47	1526874453	0.7	8.06	7.23	-1	1.3	14	0.52
30	D1	-1.3886	36.76934	41	1704.5	NE	49	5/21/2018 7:47	1526874459	0.7	11.39	3.33	-20	1.7	6	0.56
31	D1	-1.38751	36.77044	34	1706.4	NE	44	5/21/2018 7:47	1526874474	0.7	9.44	-1.95	-5	1.9	15	-0.13
32	D1	-1.38714	36.77078	27	1713.9	NE	38	5/21/2018 7:48	1526874481	0.7	7.5	-1.94	-6	7.5	7	-0.28
33	D1	-1.38672	36.77102	26	1716.2	NE	23	5/21/2018 7:48	1526874488	0.7	7.22	-0.28	-15	2.3	7	-0.04
34	D1	-1.3862	36.77111	26	1718.2	NE	4	5/21/2018 7:48	1526874496	0.7	7.22	0	-19	2	8	0
35	D1	-1.38609	36.7711	22	1718.3	NW	359	5/21/2018 7:48	1526874498	0.7	6.11	-1.11	355	0.1	2	-0.56
36	D1	-1.3857	36.77107	31	1719.8	NW	353	5/21/2018 7:48	1526874504	0.7	8.61	2.5	-6	1.5	6	0.42
37	D1	-1.38518	36.771	29	1719.6	NW	352	5/21/2018 7:48	1526874511	0.7	8.06	-0.55	-1	-0.2	7	-0.08
38	D1	-1.38469	36.77093	29	1718.7	NW	353	5/21/2018 7:48	1526874518	0.7	8.06	0	1	-0.9	7	0
39	D1	-1.38374	36.7708	22	1719.8	NW	352	5/21/2018 7:48	1526874535	0.7	6.11	-1.95	-1	1.1	17	-0.11
40	D1	-1.38322	36.77072	21	1719.3	NW	353	5/21/2018 7:49	1526874546	0.7	5.83	-0.28	1	-0.5	11	-0.03
41	D1	-1.38274	36.77067	21	1717.7	NW	352	5/21/2018 7:49	1526874555	0.7	5.83	0	-1	-1.6	9	0
42	D1	-1.38226	36.77059	28	1718.3	NW	352	5/21/2018 7:49	1526874562	0.7	7.78	1.95	0	0.6	7	0.28
43	D1	-1.38176	36.77053	16	1719.8	NW	353	5/21/2018 7:49	1526874571	0.7	4.44	-3.34	1	1.5	9	-0.37
44	D1	-1.38102	36.7704	11	1726	NW	354	5/21/2018 7:49	1526874595	0.7	3.06	-1.38	1	6.2	24	-0.06
45	D1	-1.38052	36.77033	29	1729.2	NW	353	5/21/2018 7:50	1526874606	0.7	8.06	5	-1	3.2	11	0.45
46	D1	-1.38004	36.77026	33	1731	NW	351	5/21/2018 7:50	1526874612	0.7	9.17	1.11	-2	1.8	6	0.19
47	D1	-1.37956	36.7702	11	1732.5	NW	351	5/21/2018 7:50	1526874621	0.7	3.06	-6.11	0	1.5	9	-0.68
48	D1	-1.37903	36.77012	28	1732.8	NW	354	5/21/2018 7:50	1526874635	0.7	7.78	4.72	3	0.3	14	0.34
49	D1	-1.37859	36.77006	26	1735.1	NW	349	5/21/2018 7:50	1526874643	0.7	7.22	-0.56	-5	2.3	8	-0.07
50	D1	-1.37807	36.76998	3	1735.4	NW	352	5/21/2018 7:50	1526874656	0.7	0.83	-6.39	3	0.3	13	-0.49
51	D1	-1.37746	36.7699	10	1738.3	NW	354	5/21/2018 7:51	1526874684	0.7	2.78	1.95	2	2.9	28	0.07
52	D1	-1.37695	36.76983	13	1744.3	NW	351	5/21/2018 7:51	1526874701	0.7	3.61	0.83	-3	6	17	0.05
53	D1	-1.37646	36.76976	16	1746.7	NW	350	5/21/2018 7:52	1526874721	0.7	4.44	0.83	-1	2.4	20	0.04
54	D1	-1.37591	36.76968	9	1750.5	NW	351	5/21/2018 7:52	1526874741	0.7	2.5	-1.94	1	3.8	20	-0.1
55	D1	-1.37538	36.76962	18	1756.8	NW	351	5/21/2018 7:52	1526874755	0.7	5	2.5	0	6.3	14	0.18
56	D1	-1.37436	36.76945	24	1764.6	NW	347	5/21/2018 7:52	1526874775	0.7	6.67	1.67	-4	7.8	20	0.08
57	D1	-1.37388	36.7693	29	1763.3	NW	343	5/21/2018 7:53	1526874782	0.7	8.06	1.39	-4	-1.3	7	0.2
58	D1	-1.37342	36.76915	28	1763.7	NW	339	5/21/2018 7:53	1526874789	0.7	7.78	-0.28	-4	0.4	7	-0.04
59	D1	-1.3729	36.76894	35	1766.2	NW	336	5/21/2018 7:53	1526874796	0.7	9.72	1.94	-3	2.5	7	0.28
60	D1	-1.37251	36.76868	28	1768.9	NW	306	5/21/2018 7:53	1526874802	0.7	7.78	-1.94	-30	2.7	6	-0.32
61	D1	-1.37231	36.76822	20	1773.8	NW	308	5/21/2018 7:53	1526874812	0.7	5.56	-2.22	2	4.9	10	-0.22
62	D1	-1.37224	36.76812	2	1774.4	SE	147	5/21/2018 7:57	1526875044	0.7	0.56	-5	-161	0.6	232	-0.02
63	D1	-1.37225	36.76813	3	1774.5	NW	330	5/21/2018 7:57	1526875052	0.7	0.83	0.27	183	0.1	8	0.03
64	D1	-1.37225	36.76813	4	1774.5	NE	10	5/21/2018 7:57	1526875054	0.7	1.11	0.28	-320	0	2	0.14
65	D1	-1.37156	36.76828	37	1772.8	NW	333	5/21/2018 7:57	1526875076	0.7	10.28	9.17	323	-1.7	22	0.42
66	D1	-1.37109	36.76803	44	1772.9	NW	333	5/21/2018 7:58	1526875081	0.7	12.22	1.94	0	0.1	5	0.39
67	D1	-1.37067	36.76782	49	1773.4	NW	333	5/21/2018 7:58	1526875085	0.7	13.61	1.39	0	0.5	4	0.35
68	D1	-1.37023	36.76761	48	1774.5	NW	334	5/21/2018 7:58	1526875089	0.7	13.33	-0.28	1	1.1	4	-0.07
69	D1	-1.36969	36.76742	44	1776.1	NW	349	5/21/2018 7:58	1526875094	0.7	12.22	-1.11	15	1.6	5	-0.22
70	D1	-1.36926	36.76741	42	1776.7	NE	3	5/21/2018 7:58	1526875098	0.7	11.67	-0.55	-346	0.6	4	-0.14
71	D1	-1.36906	36.76743	40	1776.6	NE	8	5/21/2018 7:58	1526875100	0.7	11.11	-0.56	5	-0.1	2	-0.28
72	D1	-1.36853	36.76754	34	1778.2	NE	12	5/21/2018 7:58	1526875106	0.7	9.44	-1.67	4	1.6	6	-0.28
73	D1	-1.36824	36.76757	26	1779.2	NW	349	5/21/2018 7:58	1526875110	0.7	7.22	-2.22	337	1	4	-0.56
74	D1	-1.36818	36.76749	23	1779.3	NW	295	5/21/2018 7:58	1526875112	0.7	6.39	-0.83	-54	0.1	2	-0.42
75	D1	-1.36798	36.76567	28	1783.9	NW	277	5/21/2018 7:58	1526875132	0.7	7.78	1.39	-18	4.6	20	0.07
76	D1	-1.36792	36.76518	33	1785.2	NW	277	5/21/2018 7:58	1526875139	0.7	9.17	1.39	0	1.3	7	0.2
77	D1	-1.36786	36.76468	44	1785.6	NW	277	5/21/2018 7:59	1526875144	0.7	12.22	3.05	0	0.4	5	0.61
78	D1	-1.36782	36.76421	49	1786.1	NW	274	5/21/2018 7:59	1526875148	0.7	13.61	1.39	-3	0.5	4	0.35
79	D1	-1.36783	36.7637	51	1786.3	SW	266	5/21/2018 7:59	1526875152	0.7	14.17	0.56	-8	0.2	4	0.14

80	D1	-1.36787	36.76318	50	1786.6	SW	265	5/21/2018 7:59	1526875156	0.7	13.89	-0.28	-1	0.3	4	-0.07
81	D1	-1.36791	36.76267	51	1786.4	SW	266	5/21/2018 7:59	1526875160	0.7	14.17	0.28	1	-0.2	4	0.07
82	D1	-1.36794	36.76216	33	1785.7	SW	266	5/21/2018 7:59	1526875165	0.7	9.17	-5	0	-0.7	5	-1
83	D1	-1.36799	36.7616	44	1786.4	SW	266	5/21/2018 7:59	1526875171	0.7	12.22	3.05	0	0.7	6	0.51
84	D1	-1.36802	36.76113	49	1787.2	SW	266	5/21/2018 7:59	1526875175	0.7	13.61	1.39	0	0.8	4	0.35
85	D1	-1.3681	36.76014	49	1788.3	SW	265	5/21/2018 7:59	1526875183	0.7	13.61	0	-1	1.1	8	0
86	D1	-1.36817	36.75885	45	1787.4	SW	266	5/21/2018 7:59	1526875197	0.7	12.5	-1.11	1	-0.9	14	-0.08
87	D1	-1.3682	36.75837	48	1787.3	SW	266	5/21/2018 8:00	1526875201	0.7	13.33	0.83	0	-0.1	4	0.21
88	D1	-1.36824	36.75787	50	1787.6	SW	266	5/21/2018 8:00	1526875205	0.7	13.89	0.56	0	0.3	4	0.14
89	D1	-1.36826	36.75739	46	1788.4	SW	267	5/21/2018 8:00	1526875209	0.7	12.78	-1.11	1	0.8	4	-0.28
90	D1	-1.3683	36.75685	40	1789.5	SW	264	5/21/2018 8:00	1526875214	0.7	11.11	-1.67	-3	1.1	5	-0.33
91	D1	-1.3683	36.75672	2	1791.1	SW	249	5/21/2018 8:00	1526875243	0.8	0.56	-10.55	-15	1.6	29	-0.36
92	D1	-1.36829	36.75647	11	1790.5	NW	303	5/21/2018 8:00	1526875254	0.8	3.06	2.5	54	-0.6	11	0.23
93	D1	-1.36822	36.75642	17	1790.6	NW	334	5/21/2018 8:00	1526875256	0.8	4.72	1.66	31	0.1	2	0.83
94	D1	-1.36807	36.75637	16	1791.4	NW	348	5/21/2018 8:01	1526875260	0.8	4.44	-0.28	14	0.8	4	-0.07
95	D1	-1.36723	36.75626	20	1791	NW	352	5/21/2018 8:01	1526875276	0.8	5.56	1.12	4	-0.4	16	0.07
96	D1	-1.36675	36.7562	28	1792.1	NW	355	5/21/2018 8:01	1526875283	0.8	7.78	2.22	3	1.1	7	0.32
97	D1	-1.36629	36.75612	19	1793.9	NW	351	5/21/2018 8:01	1526875290	0.8	5.28	-2.5	-4	1.8	7	-0.36
98	D1	-1.36578	36.75606	42	1795.2	NW	353	5/21/2018 8:01	1526875296	0.8	11.67	6.39	2	1.3	6	1.07
99	D1	-1.36527	36.756	41	1795.8	NW	354	5/21/2018 8:01	1526875301	0.8	11.39	-0.28	1	0.6	5	-0.06
100	D1	-1.36348	36.75578	27	1800.3	NW	353	5/21/2018 8:02	1526875329	0.8	7.5	-3.89	-1	4.5	28	-0.14
101	D1	-1.36312	36.75563	18	1802	NW	294	5/21/2018 8:02	1526875337	0.8	5	-2.5	-59	1.7	8	-0.31
102	D1	-1.36312	36.75554	12	1802.3	SW	267	5/21/2018 8:02	1526875340	0.8	3.33	-1.67	-27	0.3	3	-0.56
103	D1	-1.36319	36.75506	32	1801.2	SW	263	5/21/2018 8:02	1526875348	0.8	8.89	5.56	-4	-1.1	8	0.7
104	D1	-1.36326	36.75451	39	1800.7	SW	264	5/21/2018 8:02	1526875354	0.8	10.83	1.94	1	-0.5	6	0.32
105	D1	-1.36332	36.75403	38	1799.9	SW	263	5/21/2018 8:02	1526875359	0.8	10.56	-0.27	-1	-0.8	5	-0.05
106	D1	-1.36346	36.75311	36	1799.4	SW	263	5/21/2018 8:02	1526875374	0.8	10	-0.56	0	-0.5	15	-0.04
107	D1	-1.36355	36.75242	41	1798.6	SW	262	5/21/2018 8:03	1526875381	0.8	11.39	1.39	-1	-0.8	7	0.2
108	D1	-1.36362	36.7519	41	1798.9	SW	263	5/21/2018 8:03	1526875386	0.8	11.39	0	1	0.3	5	0
109	D1	-1.36367	36.75139	24	1799.4	SW	263	5/21/2018 8:03	1526875395	0.8	6.67	-4.72	0	0.5	9	-0.52
110	D1	-1.36373	36.7509	34	1799.1	SW	261	5/21/2018 8:03	1526875401	0.8	9.44	2.77	-2	-0.3	6	0.46
111	D1	-1.36385	36.74989	25	1798.5	SW	259	5/21/2018 8:03	1526875418	0.8	6.94	-2.5	-2	-0.6	17	-0.15
112	D1	-1.36392	36.74936	41	1799.5	SW	262	5/21/2018 8:03	1526875424	0.8	11.39	4.45	3	1	6	0.74
113	D1	-1.36412	36.7478	41	1797.9	SW	258	5/21/2018 8:03	1526875438	0.8	11.39	0	-4	-1.6	14	0
114	D1	-1.36424	36.74728	30	1800.6	SW	256	5/21/2018 8:04	1526875444	0.8	8.33	-3.06	-2	2.7	6	-0.51
115	D1	-1.36417	36.74704	11	1805.1	NW	348	5/21/2018 8:04	1526875451	0.8	3.06	-5.27	92	4.5	7	-0.75
116	D1	-1.36392	36.74716	37	1805.6	NE	34	5/21/2018 8:04	1526875455	0.8	10.28	7.22	-314	0.5	4	1.81
117	D1	-1.3634	36.74742	50	1804.7	NE	17	5/21/2018 8:04	1526875460	0.8	13.89	3.61	-17	-0.9	5	0.72
118	D1	-1.36303	36.74743	50	1805.5	NW	357	5/21/2018 8:04	1526875463	0.8	13.89	0	340	0.8	3	0
119	D1	-1.36279	36.74741	49	1806	NW	354	5/21/2018 8:04	1526875465	0.8	13.61	-0.28	-3	0.5	2	-0.14
120	D1	-1.36226	36.74733	39	1808.5	NW	352	5/21/2018 8:04	1526875470	0.8	10.83	-2.78	-2	2.5	5	-0.56
121	D1	-1.36172	36.74725	34	1808.9	NW	352	5/21/2018 8:04	1526875476	0.9	9.44	-1.39	0	0.4	6	-0.23
122	D1	-1.36125	36.74718	41	1810.8	NW	352	5/21/2018 8:04	1526875481	0.8	11.39	1.95	0	1.9	5	0.39
123	D1	-1.3574	36.74674	40	1811.2	NW	353	5/21/2018 8:05	1526875512	0.8	11.11	-0.28	1	0.4	31	-0.01
124	D1	-1.35688	36.74667	43	1813.1	NW	353	5/21/2018 8:05	1526875517	0.8	11.94	0.83	0	1.9	5	0.17
125	D1	-1.35633	36.74661	45	1813.8	NW	352	5/21/2018 8:05	1526875522	0.8	12.5	0.56	-1	0.7	5	0.11
126	D1	-1.35588	36.74655	46	1814.6	NW	353	5/21/2018 8:05	1526875526	0.8	12.78	0.28	1	0.8	4	0.07
127	D1	-1.35534	36.7465	41	1814.6	NW	357	5/21/2018 8:05	1526875531	0.8	11.39	-1.39	4	0	5	-0.28
128	D1	-1.35514	36.74651	39	1814.6	NE	1	5/21/2018 8:05	1526875533	0.8	10.83	-0.56	-356	0	2	-0.28
129	D1	-1.35487	36.74653	21	1814.1	NE	9	5/21/2018 8:05	1526875537	0.8	5.83	-5	8	-0.5	4	-1.25
130	D1	-1.3544	36.74342	25	1815.3	SW	263	5/21/2018 8:06	1526875597	0.8	6.94	1.11	254	1.2	60	0.02
131	D1	-1.35453	36.7425	21	1819.2	SW	261	5/21/2018 8:06	1526875617	0.9	5.83	-1.11	-2	3.9	20	-0.06
132	D1	-1.35458	36.74199	20	1822.3	SW	263	5/21/2018 8:07	1526875626	0.9	5.56	-0.27	2	3.1	9	-0.03
133	D1	-1.35465	36.74143	45	1824.5	SW	263	5/21/2018 8:07	1526875632	0.9	12.5	6.94	0	2.2	6	1.16
134	D1	-1.35472	36.74095	48	1825	SW	262	5/21/2018 8:07	1526875636	0.9	13.33	0.83	-1	0.5	4	0.21
135	D1	-1.35477	36.74042	53	1824.3	SW	264	5/21/2018 8:07	1526875640	0.9	14.72	1.39	2	-0.7	4	0.35
136	D1	-1.35481	36.73996	58	1823.7	SW	263	5/21/2018 8:07	1526875643	0.9	16.11	1.39	-1	-0.6	3	0.46
137	D1	-1.35488	36.73948	65	1824.3	SW	262	5/21/2018 8:07	1526875646	0.9	18.06	1.95	-1	0.6	3	0.65
138	D1	-1.35495	36.739	64	1825.1	SW	263	5/21/2018 8:07	1526875649	0.8	17.78	-0.28	1	0.8	3	-0.09
139	D1	-1.355	36.73852	65	1825.6	SW	264	5/21/2018 8:07	1526875652	0.8	18.06	0.28	1	0.5	3	0.09
140	D1	-1.35513	36.73747	69	1824.1	SW	264	5/21/2018 8:07	1526875658	0.8	19.17	1.11	0	-1.5	6	0.19
141	D1	-1.35524	36.73651	61	1823.9	SW	263	5/21/2018 8:07	1526875664	0.8	16.94	-2.23	-1	-0.2	6	-0.37
142	D1	-1.35542	36.73494	27	1826.5	SW	263	5/21/2018 8:07	1526875678	0.8	7.5	-9.44	0	2.6	14	-0.67
143	D1	-1.35549	36.73443	15	1826.6	SW	263	5/21/2018 8:08	1526875690	0.8	4.17	-3.33	0	0.1	12	-0.28
144	D1	-1.35555	36.7338	12	1828.5	SW	264	5/21/2018 8:08	1526875707	0.8	3.33	-0.84	1	1.9	17	-0.05
145	D1	-1.35561	36.73337	34	1829.6	SW	263	5/21/2018 8:08	1526875714	0.8	9.44	6.11	-1	1.1	7	0.87
146	D1	-1.35567	36.73289	32	1831	SW	262	5/21/2018 8:08	1526875720	0.9	8.89	-0.55	-1	1.4	6	-0.09
147	D1	-1.35574	36.73241	40	1830.3	SW	263	5/21/2018 8:08	1526875725	0.9	11.11	2.22	1	-0.7	5	0.44
148	D1	-1.35596	36.73037	60	1829.4	SW	264	5/21/2018 8:08	1526875739	0.8	16.67	5.56	1	-0.9	14	0.4
149	D1	-1.35593	36.72935	57	1833.5	NW	276	5/21/2018 8:09	1526875746	0.8	15.83	-0.84	12	4.1	7	-0.12
150	D1	-1.3558	36.72823	59	1832.9	NW	275	5/21/2018 8:09	1526875754	0.8	16.39	0.56	-1	-0.6	8	0.07
151	D1	-1.35583	36.72674	45	1840	SW	249	5/21/2018 8:09	1526875766	0.8	12.5	-3.89	-26	7.1	12	-0.32
152	D1	-1.35528	36.7264	29	1843.5	NE	3	5/21/2018 8:09	1526875780	0.8	8.06	-4.44	-246	3.5	14	-0.32
153	D1	-1.35511	36.72679	10	1839	NE	84	5/21/2018 8:09	1526875798	0.8	2.78	-5.28	81	-4.5	18	-0.29
154	D1	-1.35512	36.72712	0	1838.8	SW	254	5/21/2018 8:20	1526876456	0.9	0	-2.78	170	-0.2	658	0

Table 0.4. Normal Acceleration Analysis (Descriptive Statistics)

	Test Group 1	*Test Group 2*	*Test Group 3*
Mean	0.216666667	0.206666667	0.21
Standard Error	0.003333333	0.006666667	0.005773503
Median	0.22	0.2	0.21
Mode	0.22	0.2	#N/A
Standard Deviation	0.005773503	0.011547005	0.01
Sample Variance	3.33333E-05	0.000133333	1E-04
Kurtosis	#DIV/0!	#DIV/0!	#DIV/0!
Skewness	-1.732050808	1.732050808	1.19904E-14
Range	0.01	0.02	0.02
Minimum	0.21	0.2	0.2
Maximum	0.22	0.22	0.22
Sum	0.65	0.62	0.63
Count	3	3	3
Confidence Level(95.0%)	0.014342176	0.028684352	0.024841377

Table 0.5. Harsh Acceleration Analysis (Descriptive Statistics)

	Test Group 1	*Test Group 2*	*Test Group 3*
Mean	0.096666667	0.083333333	0.083333333
Standard Error	0.003333333	0.003333333	0.003333333
Median	0.1	0.08	0.08
Mode	0.1	0.08	0.08
Standard Deviation	0.005773503	0.005773503	0.005773503
Sample Variance	3.33333E-05	3.33333E-05	3.33333E-05
Kurtosis	#DIV/0!	#DIV/0!	#DIV/0!
Skewness	-1.732050808	1.732050808	1.732050808
Range	0.01	0.01	0.01
Minimum	0.09	0.08	0.08
Maximum	0.1	0.09	0.09
Sum	0.29	0.25	0.25
Count	3	3	3
Confidence Level(95.0%)	0.014342176	0.014342176	0.014342176

Table 0.6. Speed Analysis (Descriptive Statistics)

	Test Group 1	*Test Group 2*	*Test Group 3*
Mean	70.33333333	105	92.66666667
Standard Error	1.855921454	5.859465277	15.76212056
Median	69	107	80
Mode	#N/A	#N/A	#N/A
Standard Deviation	3.214550254	10.14889157	27.30079364
Sample Variance	10.33333333	103	745.3333333
Kurtosis	#DIV/0!	#DIV/0!	#DIV/0!
Skewness	1.545392526	-0.852357657	1.638409321
Range	6	20	50
Minimum	68	94	74
Maximum	74	114	124
Sum	211	315	278
Count	3	3	3
Confidence Level(95.0%)	7.985385511	25.21124427	67.81893104

Table 0.7. Normal Braking Analysis (Descriptive Statistics)

	Test Group 1	*Test Group 2*	*Test Group 3*
Mean	0.193333333	0.186666667	0.19
Standard Error	0.003333333	0.006666667	0.005773503
Median	0.19	0.18	0.19
Mode	0.19	0.18	#N/A
Standard Deviation	0.005773503	0.011547005	0.01
Sample Variance	3.33333E-05	0.000133333	0.0001
Kurtosis	#DIV/0!	#DIV/0!	#DIV/0!
Skewness	1.732050808	1.732050808	-2.44804E-14
Range	0.01	0.02	0.02
Minimum	0.19	0.18	0.18
Maximum	0.2	0.2	0.2
Sum	0.58	0.56	0.57
Count	3	3	3
Confidence Level(95.0%)	0.014342176	0.028684352	0.024841377

Table 0.8. Harsh Braking Analysis (Descriptive Statistics)

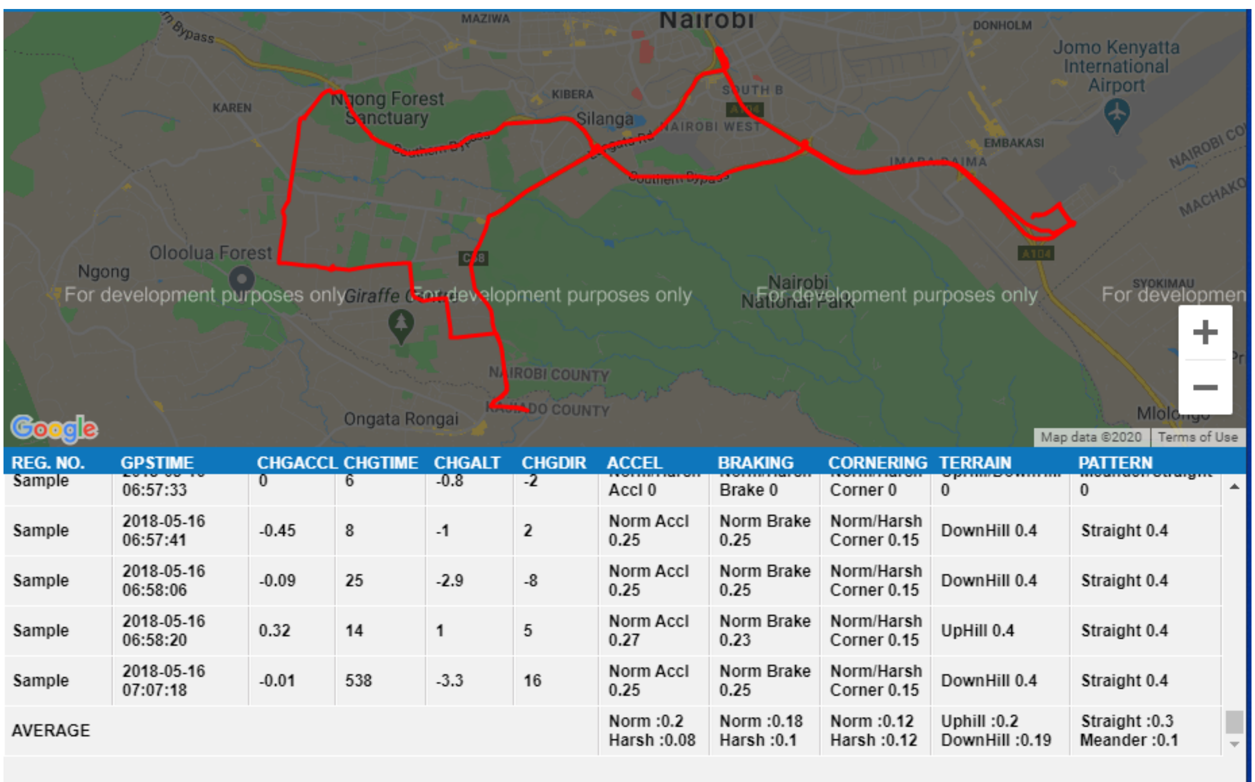
	Test Group 1	*Test Group 2*	*Test Group 3*
Mean	0.12	0.103333333	0.103333333
Standard Error	0	0.003333333	0.003333333
Median	0.12	0.1	0.1
Mode	0.12	0.1	0.1
Standard Deviation	0	0.005773503	0.005773503
Sample Variance	0	3.33333E-05	3.33333E-05
Kurtosis	#DIV/0!	#DIV/0!	#DIV/0!
Skewness	#DIV/0!	1.732050808	1.732050808
Range	0	0.01	0.01
Minimum	0.12	0.1	0.1
Maximum	0.12	0.11	0.11
Sum	0.36	0.31	0.31
Count	3	3	3
Confidence Level(95.0%)	0	0.014342176	0.014342176

Table 0.9. Normal Cornering Analysis (Descriptive Statistics)

	Test Group 1	*Test Group 2*	*Test Group 3*
Mean	0.13	0.123333333	0.123333333
Standard Error	0	0.003333333	0.003333333
Median	0.13	0.12	0.12
Mode	0.13	0.12	0.12
Standard Deviation	0	0.005773503	0.005773503
Sample Variance	0	3.33333E-05	3.33333E-05
Kurtosis	#DIV/0!	#DIV/0!	#DIV/0!
Skewness	#DIV/0!	1.732050808	1.732050808
Range	0	0.01	0.01
Minimum	0.13	0.12	0.12
Maximum	0.13	0.13	0.13
Sum	0.39	0.37	0.37
Count	3	3	3
Confidence Level(95.0%)	0	0.014342176	0.014342176

Table 0.10. Harsh Cornering Analysis (Descriptive Statistics)

	Test Group 1	*Test Group 2*	*Test Group 3*
Mean	0.14	0.126666667	0.126666667
Standard Error	0	0.006666667	0.003333333
Median	0.14	0.12	0.13
Mode	0.14	0.12	0.13
Standard Deviation	0	0.011547005	0.005773503
Sample Variance	0	0.000133333	3.33333E-05
Kurtosis	#DIV/0!	#DIV/0!	#DIV/0!
Skewness	#DIV/0!	1.732050808	-1.732050808
Range	0	0.02	0.01
Minimum	0.14	0.12	0.12
Maximum	0.14	0.14	0.13
Sum	0.42	0.38	0.38
Count	3	3	3
Confidence Level(95.0%)	0	0.028684352	0.014342176



REG. NO.	GPSTIME	CHGACCL	CHGTIME	CHGALT	CHGDIR	ACCEL	BRAKING	CORNERING	TERRAIN	PATTERN
Sample	06:57:33	0	6	-0.8	-2	Accl 0	Brake 0	Corner 0	0	0
Sample	2018-05-16 06:57:41	-0.45	8	-1	2	Norm Accl 0.25	Norm Brake 0.25	Norm/Harsh Corner 0.15	DownHill 0.4	Straight 0.4
Sample	2018-05-16 06:58:06	-0.09	25	-2.9	-8	Norm Accl 0.25	Norm Brake 0.25	Norm/Harsh Corner 0.15	DownHill 0.4	Straight 0.4
Sample	2018-05-16 06:58:20	0.32	14	1	5	Norm Accl 0.27	Norm Brake 0.23	Norm/Harsh Corner 0.15	UpHill 0.4	Straight 0.4
Sample	2018-05-16 07:07:18	-0.01	538	-3.3	16	Norm Accl 0.25	Norm Brake 0.25	Norm/Harsh Corner 0.15	DownHill 0.4	Straight 0.4
AVERAGE						Norm :0.2 Harsh :0.08	Norm :0.18 Harsh :0.1	Norm :0.12 Harsh :0.12	Uphill :0.2 DownHill :0.19	Straight :0.3 Meander :0.1

Figure 0.1. Sample Half-Dual and Half-Single Carriageway (Prestudy)

Table 0.11. Sample Data for a Test Segment in Figure 0.1 (Prestudy)

Data Point	Driver	Lat	Lon	Spd (km/h)	Alt	Dir	Dir (°)	Time	GPSTime	GPS Signal Strength	Spd (m/s)	ΔSpd (m/s^2)	ΔDir (°)	ΔAlt (m)	ΔTm (s)	Accel/ Decel (m/s^2)
1	D1	-1.39168	36.77649	0	1711.3	SW	194	5/16/2018 8:25	1526444758	0.8	0					
2	D1	-1.39167	36.7765	2	1717	NW	299	5/16/2018 8:32	1526445128	0.8	0.56	0.56	105	5.7	370	0
3	D1	-1.39163	36.77645	3	1716.8	NW	348	5/16/2018 8:32	1526445137	0.8	0.83	0.27	49	-0.2	9	0.03
4	D1	-1.39163	36.77645	2	1716.1	SE	170	5/16/2018 8:32	1526445142	0.8	0.56	-0.27	-178	-0.7	5	-0.05
5	D1	-1.39185	36.77634	6	1712.5	SW	231	5/16/2018 8:32	1526445175	0.8	1.67	1.11	61	-3.6	33	0.03
6	D1	-1.39177	36.77615	24	1713.2	NW	299	5/16/2018 8:33	1526445180	0.8	6.67	5	68	0.7	5	1
7	D1	-1.39153	36.77569	31	1714.6	NW	299	5/16/2018 8:33	1526445187	0.8	8.61	1.94	0	1.4	7	0.28
8	D1	-1.39129	36.77522	29	1716.4	NW	298	5/16/2018 8:33	1526445194	0.9	8.06	-0.55	-1	1.8	7	-0.08
9	D1	-1.39113	36.77466	7	1719.8	NW	282	5/16/2018 8:33	1526445211	0.8	1.94	-6.12	-16	3.4	17	-0.36
10	D1	-1.39107	36.77411	24	1717.6	NW	274	5/16/2018 8:33	1526445224	0.9	6.67	4.73	-8	-2.2	13	0.36
11	D1	-1.39104	36.7729	34	1717.4	NW	271	5/16/2018 8:34	1526445241	0.8	9.44	2.77	-3	-0.2	17	0.16
12	D1	-1.39101	36.77239	34	1721.5	NW	274	5/16/2018 8:34	1526445247	0.8	9.44	0	3	4.1	6	0
13	D1	-1.39096	36.77192	36	1721.5	NW	275	5/16/2018 8:34	1526445252	0.8	10	0.56	1	0	5	0.11
14	D1	-1.39092	36.77144	38	1720.3	NW	275	5/16/2018 8:34	1526445257	0.8	10.56	0.56	0	-1.2	5	0.11
15	D1	-1.39087	36.77098	37	1720.7	NW	275	5/16/2018 8:34	1526445262	0.9	10.28	-0.28	0	0.4	5	-0.06
16	D1	-1.3908	36.77049	21	1726.7	NW	279	5/16/2018 8:34	1526445269	0.9	5.83	-4.45	4	6	7	-0.64
17	D1	-1.39075	36.76994	22	1722.6	NW	271	5/16/2018 8:34	1526445282	0.8	6.11	0.28	-8	-4.1	13	0.02
18	D1	-1.39079	36.76868	33	1725.2	SW	267	5/16/2018 8:35	1526445301	0.8	9.17	3.06	-4	2.6	19	0.16
19	D1	-1.39082	36.76817	34	1721.7	SW	268	5/16/2018 8:35	1526445307	0.8	9.44	0.27	1	-3.5	6	0.04
20	D1	-1.39083	36.76769	31	1718.3	NW	274	5/16/2018 8:35	1526445313	0.8	8.61	-0.83	6	-3.4	6	-0.14
21	D1	-1.39068	36.7672	4	1724.6	NW	292	5/16/2018 8:35	1526445349	0.8	1.11	-7.5	18	6.3	36	-0.21
22	D1	-1.3906	36.76704	12	1718.7	NW	335	5/16/2018 8:36	1526445392	0.8	3.33	2.22	43	-5.9	43	0.05
23	D1	-1.39053	36.76703	14	1718.7	NE	3	5/16/2018 8:36	1526445394	0.8	3.89	0.56	-332	0	2	0.28
24	D1	-1.39044	36.76706	18	1718.7	NE	27	5/16/2018 8:36	1526445396	0.8	5	1.11	24	0	2	0.56
25	D1	-1.38999	36.76738	41	1713.9	NE	38	5/16/2018 8:36	1526445403	0.8	11.39	6.39	11	-4.8	7	0.91
26	D1	-1.38955	36.76775	46	1708.6	NE	45	5/16/2018 8:36	1526445408	0.8	12.78	1.39	7	-5.3	5	0.28
27	D1	-1.38938	36.76794	49	1707.5	NE	49	5/16/2018 8:36	1526445410	0.8	13.61	0.83	4	-1.1	2	0.42
28	D1	-1.38854	36.76943	44	1706	NE	47	5/16/2018 8:37	1526445423	0.8	12.22	-1.39	-2	-1.5	13	-0.11
29	D1	-1.38816	36.76981	44	1705.7	NE	45	5/16/2018 8:37	1526445428	0.8	12.22	0	-2	-0.3	5	0
30	D1	-1.38776	36.77021	44	1707.3	NE	45	5/16/2018 8:37	1526445433	0.8	12.22	0	0	1.6	5	0
31	D1	-1.38736	36.77059	43	1708.7	NE	43	5/16/2018 8:37	1526445438	0.8	11.94	-0.28	-2	1.4	5	-0.06
32	D1	-1.38699	36.77089	36	1711.9	NE	35	5/16/2018 8:37	1526445443	0.8	10	-1.94	-8	3.2	5	-0.39
33	D1	-1.3865	36.77108	35	1714.8	NE	16	5/16/2018 8:37	1526445449	0.8	9.72	-0.28	-19	2.9	6	-0.05
34	D1	-1.38623	36.77111	37	1717.9	NE	4	5/16/2018 8:37	1526445452	0.8	10.28	0.56	-12	3.1	3	0.19
35	D1	-1.38603	36.77111	41	1719	NW	359	5/16/2018 8:37	1526445454	0.8	11.39	1.11	355	1.1	2	0.56
36	D1	-1.38548	36.77104	46	1722.6	NW	352	5/16/2018 8:37	1526445459	0.8	12.78	1.39	-7	3.6	5	0.28
37	D1	-1.38495	36.77096	41	1720.6	NW	352	5/16/2018 8:37	1526445464	0.8	11.39	-1.39	0	-2	5	-0.28
38	D1	-1.38341	36.77075	36	1716.3	NW	354	5/16/2018 8:38	1526445481	0.8	10	-1.39	2	-4.3	17	-0.08
39	D1	-1.38288	36.77068	30	1716.9	NW	353	5/16/2018 8:38	1526445489	0.8	8.33	-1.67	-1	0.6	8	-0.21
40	D1	-1.38238	36.77061	35	1717	NW	352	5/16/2018 8:38	1526445496	0.8	9.72	1.39	-1	0.1	7	0.2
41	D1	-1.3819	36.77054	39	1716.6	NW	352	5/16/2018 8:38	1526445501	0.8	10.83	1.11	0	-0.4	5	0.22
42	D1	-1.38143	36.77047	37	1716.6	NW	353	5/16/2018 8:38	1526445506	0.8	10.28	-0.55	1	0	5	-0.11
43	D1	-1.38092	36.7704	21	1719.4	NW	352	5/16/2018 8:38	1526445513	0.8	5.83	-4.45	-1	2.8	7	-0.64
44	D1	-1.38038	36.77031	36	1722.3	NW	350	5/16/2018 8:38	1526445522	0.8	10	4.17	-2	2.9	9	0.46
45	D1	-1.37988	36.77024	42	1724.5	NW	352	5/16/2018 8:38	1526445527	0.8	11.67	1.67	2	2.2	5	0.33
46	D1	-1.37828	36.77002	44	1725.8	NW	352	5/16/2018 8:39	1526445541	0.8	12.22	0.55	0	1.3	14	0.04
47	D1	-1.37776	36.76994	39	1735.4	NW	352	5/16/2018 8:39	1526445546	0.8	10.83	-1.39	0	9.6	5	-0.28
48	D1	-1.37726	36.76988	33	1741.6	NW	353	5/16/2018 8:39	1526445552	0.8	9.17	-1.66	1	6.2	6	-0.28
49	D1	-1.37675	36.76981	29	1748.6	NW	353	5/16/2018 8:39	1526445559	0.8	8.06	-1.11	0	7	7	-0.16
50	D1	-1.37625	36.76974	31	1754.5	NW	352	5/16/2018 8:39	1526445566	0.8	8.61	0.55	-1	5.9	7	0.08
51	D1	-1.37576	36.76968	34	1757.8	NW	352	5/16/2018 8:39	1526445572	0.8	9.44	0.83	0	3.3	6	0.14
52	D1	-1.37524	36.7696	27	1761.7	NW	350	5/16/2018 8:39	1526445580	0.8	7.5	-1.94	-2	3.9	8	-0.24
53	D1	-1.37475	36.76952	35	1763.2	NW	351	5/16/2018 8:39	1526445586	0.8	9.72	2.22	1	1.5	6	0.37
54	D1	-1.37303	36.76901	49	1764.8	NW	336	5/16/2018 8:40	1526445602	0.8	13.61	3.89	-15	1.6	16	0.24
55	D1	-1.37255	36.76878	37	1770.9	NW	334	5/16/2018 8:40	1526445607	0.8	10.28	-3.33	-2	6.1	5	-0.67
56	D1	-1.37208	36.76854	35	1772.1	NW	332	5/16/2018 8:40	1526445614	0.8	9.72	-0.56	-2	1.2	7	-0.08
57	D1	-1.37164	36.76832	42	1772.9	NW	333	5/16/2018 8:40	1526445619	0.8	11.67	1.95	1	0.8	5	0.39
58	D1	-1.37123	36.76811	48	1773.5	NW	334	5/16/2018 8:40	1526445623	0.8	13.33	1.66	1	0.6	4	0.42
59	D1	-1.37078	36.76788	51	1774.9	NW	333	5/16/2018 8:40	1526445627	0.8	14.17	0.84	-1	1.4	4	0.21
60	D1	-1.36986	36.76747	49	1776.6	NW	342	5/16/2018 8:40	1526445635	0.8	13.61	-0.56	9	1.7	8	-0.07
61	D1	-1.36937	36.76741	49	1776.9	NE	1	5/16/2018 8:40	1526445639	0.8	13.61	0	-341	0.3	4	0
62	D1	-1.3689	36.76747	46	1777.5	NE	10	5/16/2018 8:40	1526445643	0.8	12.78	-0.83	9	0.6	4	-0.21
63	D1	-1.36837	36.76757	43	1778.2	NE	11	5/16/2018 8:40	1526445648	0.8	11.94	-0.84	1	0.7	5	-0.17
64	D1	-1.36683	36.76729	45	1780.7	NW	332	5/16/2018 8:41	1526445662	0.8	12.5	0.56	321	2.5	14	0.04
65	D1	-1.3664	36.76706	37	1782.3	NW	330	5/16/2018 8:41	1526445667	0.8	10.28	-2.22	-2	1.6	5	-0.44
66	D1	-1.36595	36.7668	30	1782.3	NW	332	5/16/2018 8:41	1526445677	0.8	8.33	-1.95	2	0	10	-0.2
67	D1	-1.36549	36.76654	37	1780.2	NW	331	5/16/2018 8:41	1526445683	0.8	10.28	1.95	-1	-2.1	6	0.33
68	D1	-1.36508	36.76632	37	1779.3	NW	331	5/16/2018 8:41	1526445688	0.8	10.28	0	0	-0.9	5	0
69	D1	-1.36462	36.76607	32	1778.6	NW	331	5/16/2018 8:41	1526445694	0.8	8.89	-1.39	0	-0.7	6	-0.23
70	D1	-1.36418	36.76579	23	1780.6	NW	325	5/16/2018 8:41	1526445705	0.8	6.39	-2.5	-6	2	11	-0.23
71	D1	-1.3631	36.76484	43	1783.7	NW	319	5/16/2018 8:42	1526445722	0.8	11.94	5.55	-6	3.1	17	0.33
72	D1	-1.36268	36.76447	46	1785.2	NW	318	5/16/2018 8:42	1526445727	0.8	12.78	0.84	-1	1.5	5	0.17
73	D1	-1.36231	36.76415	49	1786.1	NW	318	5/16/2018 8:42	1526445731	0.8	13.61	0.83	0	0.9	4	0.21
74	D1	-1.36193	36.7638	52	1786.8	NW	318	5/16/2018 8:42	1526445735	0.8	14.44	0.83	0	0.7	4	0.21
75	D1	-1.36155	36.76346	49	1787.9	NW	318	5/16/2018 8:42	1526445739	0.8	13.61	-0.83	0	1.1	4	-0.21
76	D1	-1.36118	36.76314	48	1789.6	NW	319	5/16/2018 8:42	1526445743	0.8	13.33	-0.28	1	1.7	4	-0.07
77	D1	-1.36077	36.76284	50	1791.3	NW	331	5/16/2018 8:42	1526445747	0.8	13.89	0.56	12	1.7	4	0.14
78	D1	-1.36029	36.7627	49	1792.3	NW	349	5/16/2018 8:42	1526445751	0.8	13.61	-0.28	18	1	4	-0.07
79	D1	-1.3598	36.76264	52	1791.9	NW	355	5/16/2018 8:42	1526445755	0.8	14.44	0.83	6	-0.4	4	0.21

80	D1	-1.35929	36.76261	51	1791.5	NW	357	5/16/2018 8:42	1526445759	0.8	14.17	-0.27	2	-0.4	4	-0.07
81	D1	-1.35481	36.76185	39	1793.2	NE	3	5/16/2018 8:43	1526445822	0.8	10.83	-3.34	-354	1.7	63	-0.05
82	D1	-1.35436	36.76196	49	1790.2	NE	19	5/16/2018 8:43	1526445826	0.8	13.61	2.78	16	-3	4	0.7
83	D1	-1.35385	36.76217	57	1786	NE	25	5/16/2018 8:43	1526445830	0.8	15.83	2.22	6	-4.2	4	0.56
84	D1	-1.35225	36.76285	30	1783.2	NE	12	5/16/2018 8:44	1526445844	0.9	8.33	-7.5	-13	-2.8	14	-0.54
85	D1	-1.35174	36.76293	29	1793.8	NE	11	5/16/2018 8:44	1526445853	0.8	8.06	-0.27	-1	10.6	9	-0.03
86	D1	-1.35123	36.76308	38	1797.3	NE	19	5/16/2018 8:44	1526445859	0.8	10.56	2.5	8	3.5	6	0.42
87	D1	-1.35077	36.76333	43	1797.1	NE	32	5/16/2018 8:44	1526445864	0.8	11.94	1.38	13	-0.2	5	0.28
88	D1	-1.3503	36.76365	48	1795.2	NE	33	5/16/2018 8:44	1526445869	0.8	13.33	1.39	1	-1.9	5	0.28
89	D1	-1.34987	36.76395	55	1793.1	NE	35	5/16/2018 8:44	1526445873	0.8	15.28	1.95	2	-2.1	4	0.49
90	D1	-1.34939	36.76429	60	1790.9	NE	35	5/16/2018 8:44	1526445877	0.8	16.67	1.39	0	-2.2	4	0.35
91	D1	-1.34898	36.76454	62	1789.9	NE	28	5/16/2018 8:44	1526445880	0.8	17.22	0.55	-7	-1	3	0.18
92	D1	-1.34843	36.76473	56	1790.9	NE	16	5/16/2018 8:44	1526445884	0.8	15.56	-1.66	-12	1	4	-0.42
93	D1	-1.34794	36.76488	48	1793.8	NE	18	5/16/2018 8:44	1526445888	0.8	13.33	-2.23	2	2.9	4	-0.56
94	D1	-1.34707	36.76521	3	1794.9	NE	20	5/16/2018 8:45	1526445902	0.8	0.83	-12.5	2	1.1	14	-0.89
95	D1	-1.34658	36.76539	22	1792.8	NE	20	5/16/2018 8:45	1526445917	0.8	6.11	5.28	0	-2.1	15	0.35
96	D1	-1.3462	36.76551	10	1791	NE	21	5/16/2018 8:45	1526445950	0.9	2.78	-3.33	1	-1.8	33	-0.1
97	D1	-1.34557	36.76574	30	1793.6	NE	17	5/16/2018 8:46	1526445964	0.8	8.33	5.55	-4	2.6	14	0.4
98	D1	-1.34508	36.76586	33	1797	NE	15	5/16/2018 8:46	1526445971	0.8	9.17	0.84	-2	3.4	7	0.12
99	D1	-1.34462	36.76603	42	1796.3	NE	21	5/16/2018 8:46	1526445976	0.8	11.67	2.5	6	-0.7	5	0.5
100	D1	-1.34367	36.76636	54	1796.4	NE	18	5/16/2018 8:46	1526445984	0.8	15	3.33	-3	0.1	8	0.42
101	D1	-1.34317	36.76653	50	1796.8	NE	18	5/16/2018 8:46	1526445988	0.8	13.89	-1.11	0	0.4	4	-0.28
102	D1	-1.34269	36.7666	36	1796.7	NW	356	5/16/2018 8:46	1526445993	0.8	10	-3.89	338	-0.1	5	-0.78
103	D1	-1.34246	36.76659	30	1796.6	NE	6	5/16/2018 8:46	1526445996	0.8	8.33	-1.67	-350	-0.1	3	-0.56
104	D1	-1.3423	36.76671	29	1797.2	NE	59	5/16/2018 8:46	1526445999	0.8	8.06	-0.27	53	0.6	3	-0.09
105	D1	-1.34229	36.76686	31	1797.4	SE	92	5/16/2018 8:46	1526446001	0.8	8.61	0.55	33	0.2	2	0.27
106	D1	-1.34223	36.76736	46	1796.5	NE	70	5/16/2018 8:46	1526446006	0.8	12.78	4.17	-22	-0.9	5	0.83
107	D1	-1.34203	36.76786	58	1793.9	NE	68	5/16/2018 8:46	1526446010	0.8	16.11	3.33	-2	-2.6	4	0.83
108	D1	-1.3409	36.76969	46	1787.7	NE	55	5/16/2018 8:47	1526446024	0.8	12.78	-3.33	-13	-6.2	14	-0.24
109	D1	-1.34062	36.77011	38	1787.5	NE	57	5/16/2018 8:47	1526446029	0.8	10.56	-2.22	2	-0.2	5	-0.44
110	D1	-1.34032	36.77051	27	1785.5	NE	54	5/16/2018 8:47	1526446039	0.8	7.5	-3.06	-3	-2	10	-0.31
111	D1	-1.34002	36.77094	28	1783.8	NE	54	5/16/2018 8:47	1526446048	0.8	7.78	0.28	0	-1.7	9	0.03
112	D1	-1.33975	36.77132	44	1781.5	NE	56	5/16/2018 8:47	1526446053	0.8	12.22	4.44	2	-2.3	5	0.89
113	D1	-1.33945	36.77175	55	1779.8	NE	53	5/16/2018 8:47	1526446057	0.8	15.28	3.06	-3	-1.7	4	0.77
114	D1	-1.3391	36.7722	56	1778.5	NE	52	5/16/2018 8:47	1526446061	0.8	15.56	0.28	-1	-1.3	4	0.07
115	D1	-1.33877	36.77265	54	1775.7	NE	54	5/16/2018 8:47	1526446065	0.8	15	-0.56	2	-2.8	4	-0.14
116	D1	-1.33846	36.77307	34	1771.7	NE	55	5/16/2018 8:47	1526446070	0.8	9.44	-5.56	1	-4	5	-1.11
117	D1	-1.33745	36.77431	67	1770.9	NE	52	5/16/2018 8:48	1526446084	0.8	18.61	9.17	-3	-0.8	14	0.66
118	D1	-1.33712	36.77472	71	1769.9	NE	52	5/16/2018 8:48	1526446087	0.8	19.72	1.11	0	-1	3	0.37
119	D1	-1.33678	36.77516	74	1769.9	NE	52	5/16/2018 8:48	1526446090	0.8	20.56	0.84	0	0	3	0.28
120	D1	-1.33643	36.7756	76	1771.3	NE	53	5/16/2018 8:48	1526446093	0.8	21.11	0.55	1	1.4	3	0.18
121	D1	-1.33609	36.77607	76	1773.3	NE	55	5/16/2018 8:48	1526446096	0.8	21.11	0	2	2	3	0
122	D1	-1.33577	36.77656	78	1775.3	NE	59	5/16/2018 8:48	1526446099	0.8	21.67	0.56	4	2	3	0.19
123	D1	-1.33399	36.77966	86	1775.4	NE	61	5/16/2018 8:48	1526446116	0.8	23.89	2.22	2	0.1	17	0.13
124	D1	-1.33369	36.7802	82	1773.9	NE	61	5/16/2018 8:48	1526446119	0.8	22.78	-1.11	0	-1.5	3	-0.37
125	D1	-1.33344	36.78066	64	1772.1	NE	62	5/16/2018 8:48	1526446122	0.8	17.78	-5	1	-1.8	3	-1.67
126	D1	-1.33319	36.7811	38	1768.6	NE	61	5/16/2018 8:48	1526446127	0.8	10.56	-7.22	-1	-3.5	5	-1.44
127	D1	-1.33275	36.7818	6	1763.3	NE	65	5/16/2018 8:49	1526446143	0.8	1.67	-8.89	4	-5.3	16	-0.56
128	D1	-1.33217	36.78275	23	1760.3	NE	60	5/16/2018 8:51	1526446263	0.8	6.39	4.72	-5	-3	120	0.04
129	D1	-1.33192	36.78318	30	1758.2	NE	61	5/16/2018 8:51	1526446271	0.8	8.33	1.94	1	-2.1	8	0.24
130	D1	-1.3317	36.7836	29	1758.2	NE	61	5/16/2018 8:51	1526446277	0.8	8.06	-0.27	0	0	6	-0.04
131	D1	-1.33144	36.78402	28	1756.9	NE	61	5/16/2018 8:51	1526446284	0.8	7.78	-0.28	0	-1.3	7	-0.04
132	D1	-1.33115	36.78454	17	1753	NE	61	5/16/2018 8:51	1526446303	0.8	4.72	-3.06	0	-3.9	19	-0.16
133	D1	-1.33085	36.78511	4	1751.3	NE	69	5/16/2018 8:52	1526446323	0.8	1.11	-3.61	8	-1.7	20	-0.18
134	D1	-1.33046	36.78576	27	1747.5	NE	59	5/16/2018 8:53	1526446380	0.8	7.5	6.39	-10	-3.8	57	0.11
135	D1	-1.3302	36.78622	38	1747	NE	59	5/16/2018 8:53	1526446386	0.8	10.56	3.06	0	-0.5	6	0.51
136	D1	-1.32995	36.78666	37	1746.7	NE	61	5/16/2018 8:53	1526446391	0.8	10.28	-0.28	2	-0.3	5	-0.06
137	D1	-1.32969	36.78712	26	1746.4	NE	61	5/16/2018 8:53	1526446399	0.8	7.22	-3.06	0	-0.3	8	-0.38
138	D1	-1.32943	36.78757	23	1745.7	NE	61	5/16/2018 8:53	1526446407	0.8	6.39	-0.83	0	-0.7	8	-0.1
139	D1	-1.32917	36.78801	24	1744.4	NE	60	5/16/2018 8:53	1526446416	0.8	6.67	0.28	-1	-1.3	9	0.03
140	D1	-1.32891	36.78848	3	1743.5	NE	61	5/16/2018 8:54	1526446444	0.8	0.83	-5.84	1	-0.9	28	-0.21
141	D1	-1.32851	36.78905	11	1739.5	NE	57	5/16/2018 8:55	1526446535	0.8	3.06	2.23	-4	-4	91	0.02
142	D1	-1.32821	36.78954	26	1740.1	NE	63	5/16/2018 8:55	1526446552	0.8	7.22	4.16	6	0.6	17	0.24
143	D1	-1.32801	36.79001	4	1740.2	NE	70	5/16/2018 8:56	1526446565	0.8	1.11	-6.11	7	0.1	13	-0.47
144	D1	-1.32778	36.79057	7	1741.6	NE	64	5/16/2018 8:56	1526446595	0.8	1.94	0.83	-6	1.4	30	0.03
145	D1	-1.32746	36.79113	34	1731.8	NE	61	5/16/2018 8:57	1526446634	0.8	9.44	7.5	-3	-9.8	39	0.19
146	D1	-1.32722	36.79155	27	1729.4	NE	60	5/16/2018 8:57	1526446640	0.8	7.5	-1.94	-1	-2.4	6	-0.32
147	D1	-1.32695	36.792	24	1727.1	NE	60	5/16/2018 8:57	1526446650	0.8	6.67	-0.83	0	-2.3	10	-0.08
148	D1	-1.32669	36.79245	24	1725.8	NE	61	5/16/2018 8:57	1526446658	0.8	6.67	0	1	-1.3	8	0
149	D1	-1.32608	36.79348	29	1722	NE	61	5/16/2018 8:58	1526446684	0.8	8.06	1.39	0	-3.8	26	0.05
150	D1	-1.32582	36.7939	38	1720.7	NE	56	5/16/2018 8:58	1526446690	0.8	10.56	2.5	-5	-1.3	6	0.42
151	D1	-1.32559	36.7943	51	1719.1	NE	61	5/16/2018 8:58	1526446694	0.8	14.17	3.61	5	-1.6	4	0.9
152	D1	-1.32535	36.79473	44	1716.8	NE	61	5/16/2018 8:58	1526446698	0.8	12.22	-1.95	0	-2.3	4	-0.49
153	D1	-1.32503	36.79496	35	1714.4	NW	352	5/16/2018 8:58	1526446703	0.8	9.72	-2.5	291	-2.4	5	-0.5
154	D1	-1.32456	36.7945	48	1713.7	NW	308	5/16/2018 8:58	1526446709	0.8	13.33	3.61	-44	-0.7	6	0.6
155	D1	-1.32442	36.7943	45	1713.6	NW	303	5/16/2018 8:58	1526446711	0.8	12.5	-0.83	-5	-0.1	2	-0.42
156	D1	-1.32437	36.79402	38	1712.5	SW	258	5/16/2018 8:58	1526446714	0.8	10.56	-1.94	-45	-1.1	3	-0.65
157	D1	-1.32478	36.7939	31	1713.1	SE	155	5/16/2018 8:58	1526446720	0.8	8.61	-1.95	-103	0.6	6	-0.33
158	D1	-1.32521	36.79426	42	1716.9	SE	139	5/16/2018 8:58	1526446727	0.8	11.67	3.06	-16	3.8	7	0.44
159	D1	-1.32561	36.79464	57	1716.5	SE	135	5/16/2018 8:58	1526446731	0.9	15.83	4.16	-4	-0.4	4	1.04
160	D1	-1.32727	36.79661	81	1710.9	SE	128	5/16/2018 8:59	1526446745	0.8	22.5	6.67	-7	-5.6	14	0.48
161	D1	-1.32763	36.7971	80	1710.9	SE	124	5/16/2018 8:59	1526446748	0.8	22.22	-0.28	-4	0	3	-0.09
162	D1	-1.328	36.79761	85	1711.3	SE	127	5/16/2018 8:59	1526446751	0.8	23.61	1.39	3	0.4	3	0.46
163	D1	-1.32905	36.79894	88	1711.1	SE	130	5/16/2018 8:59	1526446759	0.8	24.44	0.83	3	-0.2	8	0.1

164	D1	-1.32934	36.79929	91	1710.8	SE	129	5/16/2018 8:59	1526446761	0.8	25.28	0.84	-1	-0.3	2	0.42
165	D1	-1.33047	36.80066	87	1706.2	SE	130	5/16/2018 8:59	1526446769	0.7	24.17	-1.11	1	-4.6	8	-0.14
166	D1	-1.33199	36.80272	98	1697.3	SE	119	5/16/2018 8:59	1526446780	0.7	27.22	3.05	-11	-8.9	11	0.28
167	D1	-1.33221	36.80315	96	1695.2	SE	115	5/16/2018 8:59	1526446782	0.7	26.67	-0.55	-4	-2.1	2	-0.27
168	D1	-1.33214	36.81952	79	1671.8	SE	96	5/16/2018 9:01	1526446864	0.7	21.94	-4.73	-19	-23.4	82	-0.06
169	D1	-1.33224	36.8201	79	1670.8	SE	102	5/16/2018 9:01	1526446867	0.7	21.94	0	6	-1	3	0
170	D1	-1.33238	36.82067	78	1669.5	SE	105	5/16/2018 9:01	1526446870	0.7	21.67	-0.27	3	-1.3	3	-0.09
171	D1	-1.33254	36.82124	79	1668	SE	104	5/16/2018 9:01	1526446873	0.7	21.94	0.27	-1	-1.5	3	0.09
172	D1	-1.33268	36.8218	78	1666.3	SE	102	5/16/2018 9:01	1526446876	0.7	21.67	-0.27	-2	-1.7	3	-0.09
173	D1	-1.33277	36.82237	77	1665.2	SE	98	5/16/2018 9:01	1526446879	0.7	21.39	-0.28	-4	-1.1	3	-0.09
174	D1	-1.33282	36.82293	76	1664.8	SE	93	5/16/2018 9:01	1526446882	0.8	21.11	-0.28	-5	-0.4	3	-0.09
175	D1	-1.33281	36.82351	79	1664.8	NE	87	5/16/2018 9:01	1526446885	0.7	21.94	0.83	-6	0	3	0.28
176	D1	-1.33275	36.82409	78	1664.4	NE	82	5/16/2018 9:01	1526446888	0.7	21.67	-0.27	-5	-0.4	3	-0.09
177	D1	-1.33263	36.82465	77	1664.3	NE	77	5/16/2018 9:01	1526446891	0.7	21.39	-0.28	-5	-0.1	3	-0.09
178	D1	-1.33226	36.82576	78	1664.1	NE	67	5/16/2018 9:01	1526446897	0.7	21.67	0.28	-10	-0.2	6	0.05
179	D1	-1.33199	36.82629	81	1664	NE	62	5/16/2018 9:01	1526446900	0.7	22.5	0.83	-5	-0.1	3	0.28
180	D1	-1.33168	36.82682	81	1664.2	NE	59	5/16/2018 9:01	1526446903	0.7	22.5	0	-3	0.2	3	0
181	D1	-1.33136	36.82732	79	1663.8	NE	58	5/16/2018 9:01	1526446906	0.7	21.94	-0.56	-1	-0.4	3	-0.19
182	D1	-1.33104	36.82782	79	1663.4	NE	59	5/16/2018 9:01	1526446909	0.7	21.94	0	1	-0.4	3	0
183	D1	-1.32984	36.83152	105	1660.1	NE	80	5/16/2018 9:02	1526446926	0.7	29.17	7.23	21	-3.3	17	0.43
184	D1	-1.32949	36.83355	103	1661	NE	81	5/16/2018 9:02	1526446934	0.7	28.61	-0.56	1	0.9	8	-0.07
185	D1	-1.3294	36.83406	103	1661.2	NE	80	5/16/2018 9:02	1526446936	0.7	28.61	0	-1	0.2	2	0
186	D1	-1.32932	36.83455	99	1661.3	NE	80	5/16/2018 9:02	1526446938	0.8	27.5	-1.11	0	0.1	2	-0.56
187	D1	-1.32924	36.83499	90	1661.3	NE	80	5/16/2018 9:02	1526446940	0.8	25	-2.5	0	0	2	-1.25
188	D1	-1.32913	36.83556	77	1660.7	NE	79	5/16/2018 9:02	1526446943	0.7	21.39	-3.61	-1	-0.6	3	-1.2
189	D1	-1.32903	36.83611	76	1660.1	NE	80	5/16/2018 9:02	1526446946	0.7	21.11	-0.28	1	-0.6	3	-0.09
190	D1	-1.32893	36.83668	78	1659.6	NE	80	5/16/2018 9:02	1526446949	0.7	21.67	0.56	0	-0.5	3	0.19
191	D1	-1.32882	36.83726	79	1659.2	NE	80	5/16/2018 9:02	1526446952	0.7	21.94	0.27	0	-0.4	3	0.09
192	D1	-1.32871	36.83785	81	1658.6	NE	80	5/16/2018 9:02	1526446955	0.7	22.5	0.56	0	-0.6	3	0.19
193	D1	-1.32859	36.83846	84	1657.9	NE	79	5/16/2018 9:02	1526446958	0.7	23.33	0.83	-1	-0.7	3	0.28
194	D1	-1.32827	36.84022	93	1657.9	NE	80	5/16/2018 9:02	1526446966	0.7	25.83	2.5	1	0	8	0.31
195	D1	-1.32819	36.84068	94	1658	NE	80	5/16/2018 9:02	1526446968	0.7	26.11	0.28	0	0.1	2	0.14
196	D1	-1.3281	36.84115	96	1658.1	NE	80	5/16/2018 9:02	1526446970	0.7	26.67	0.56	0	0.1	2	0.28
197	D1	-1.32801	36.84163	97	1658.1	NE	79	5/16/2018 9:02	1526446972	0.7	26.94	0.27	-1	0	2	0.14
198	D1	-1.32791	36.84211	99	1658	NE	78	5/16/2018 9:02	1526446974	0.7	27.5	0.56	-1	-0.1	2	0.28
199	D1	-1.32574	36.84615	89	1654.5	NE	47	5/16/2018 9:03	1526446993	0.7	24.72	-2.78	-31	-3.5	19	-0.15
200	D1	-1.3242	36.84742	58	1654	NE	32	5/16/2018 9:03	1526447004	0.7	16.11	-8.61	-15	-0.5	11	-0.78
201	D1	-1.32384	36.84752	50	1653.6	NE	4	5/16/2018 9:03	1526447007	0.7	13.89	-2.22	-28	-0.4	3	-0.74
202	D1	-1.3236	36.84747	49	1653.8	NW	343	5/16/2018 9:03	1526447009	0.7	13.61	-0.28	339	0.2	2	-0.14
203	D1	-1.32336	36.8472	48	1653.9	NW	296	5/16/2018 9:03	1526447012	0.7	13.33	-0.28	-47	0.1	3	-0.09
204	D1	-1.32334	36.84694	51	1654	SW	267	5/16/2018 9:03	1526447014	0.7	14.17	0.84	-29	0.1	2	0.42
205	D1	-1.32344	36.84669	51	1654.4	SW	238	5/16/2018 9:03	1526447016	0.8	14.17	0	-29	0.4	2	0
206	D1	-1.32364	36.84652	51	1654	SW	209	5/16/2018 9:03	1526447018	0.7	14.17	0	-29	-0.4	2	0
207	D1	-1.32389	36.84648	50	1653.9	S	180	5/16/2018 9:03	1526447020	0.7	13.89	-0.28	-29	-0.1	2	-0.14
208	D1	-1.32414	36.84657	51	1654.3	SE	152	5/16/2018 9:03	1526447022	0.7	14.17	0.28	-28	0.4	2	0.14
209	D1	-1.32435	36.84676	57	1654.1	SE	133	5/16/2018 9:03	1526447024	0.7	15.83	1.66	-19	-0.2	2	0.83
210	D1	-1.32454	36.84701	61	1654.3	SE	126	5/16/2018 9:03	1526447026	0.7	16.94	1.11	-7	0.2	2	0.56
211	D1	-1.32483	36.84743	69	1653.9	SE	123	5/16/2018 9:03	1526447029	0.7	19.17	2.23	-3	-0.4	3	0.74
212	D1	-1.32511	36.84791	74	1652.3	SE	121	5/16/2018 9:03	1526447032	0.7	20.56	1.39	-2	-1.6	3	0.46
213	D1	-1.3264	36.85011	72	1651.4	SE	120	5/16/2018 9:04	1526447046	0.7	20	-0.56	-1	-0.9	14	-0.04
214	D1	-1.32666	36.85056	70	1657.7	SE	120	5/16/2018 9:04	1526447049	0.7	19.44	-0.56	0	6.3	3	-0.19
215	D1	-1.32693	36.85101	74	1659	SE	121	5/16/2018 9:04	1526447052	0.7	20.56	1.12	1	1.3	3	0.37
216	D1	-1.3272	36.85148	72	1657.9	SE	120	5/16/2018 9:04	1526447055	0.8	20	-0.56	-1	-1.1	3	-0.19
217	D1	-1.32746	36.85193	68	1656.6	SE	120	5/16/2018 9:04	1526447058	0.7	18.89	-1.11	0	-1.3	3	-0.37
218	D1	-1.3277	36.85236	65	1655.6	SE	120	5/16/2018 9:04	1526447061	0.7	18.06	-0.83	0	-1	3	-0.28
219	D1	-1.32795	36.85279	66	1655.4	SE	121	5/16/2018 9:04	1526447064	0.7	18.33	0.27	1	-0.2	3	0.09
220	D1	-1.3282	36.85323	66	1655.6	SE	121	5/16/2018 9:04	1526447067	0.7	18.33	0	0	0.2	3	0
221	D1	-1.32846	36.85365	65	1655.2	SE	120	5/16/2018 9:04	1526447070	0.7	18.06	-0.27	-1	-0.4	3	-0.09
222	D1	-1.32869	36.85406	63	1654.8	SE	119	5/16/2018 9:04	1526447073	0.7	17.5	-0.56	-1	-0.4	3	-0.19
223	D1	-1.32898	36.85456	58	1654.1	SE	120	5/16/2018 9:04	1526447077	0.7	16.11	-1.39	1	-0.7	4	-0.35
224	D1	-1.32927	36.85505	56	1653.3	SE	120	5/16/2018 9:04	1526447081	0.7	15.56	-0.55	0	-0.8	4	-0.14
225	D1	-1.32955	36.85552	54	1652.2	SE	122	5/16/2018 9:04	1526447085	0.9	15	-0.56	2	-1.1	4	-0.14
226	D1	-1.32984	36.85601	60	1652	SE	119	5/16/2018 9:04	1526447089	0.7	16.67	1.67	-3	-0.2	4	0.42
227	D1	-1.33007	36.85642	64	1652.3	SE	120	5/16/2018 9:04	1526447092	0.7	17.78	1.11	1	0.3	3	0.37
228	D1	-1.33091	36.85852	63	1653.2	SE	105	5/16/2018 9:05	1526447106	0.7	17.5	-0.28	-15	0.9	14	-0.02
229	D1	-1.33101	36.85898	65	1651.7	SE	100	5/16/2018 9:05	1526447109	0.7	18.06	0.56	-5	-1.5	3	0.19
230	D1	-1.33109	36.85947	67	1650.9	SE	98	5/16/2018 9:05	1526447112	0.8	18.61	0.55	-2	-0.8	3	0.18
231	D1	-1.33114	36.85999	72	1650.8	SE	94	5/16/2018 9:05	1526447115	0.8	20	1.39	-4	-0.1	3	0.46
232	D1	-1.33116	36.86055	76	1650.8	E	90	5/16/2018 9:05	1526447118	0.8	21.11	1.11	-4	0	3	0.37
233	D1	-1.33114	36.86094	79	1650.5	NE	87	5/16/2018 9:05	1526447120	0.9	21.94	0.83	-3	-0.3	2	0.42
234	D1	-1.3311	36.86134	80	1649.6	NE	84	5/16/2018 9:05	1526447122	0.8	22.22	0.28	-3	-0.9	2	0.14
235	D1	-1.33102	36.86194	81	1648.4	NE	82	5/16/2018 9:05	1526447125	0.8	22.5	0.28	-2	-1.2	3	0.09
236	D1	-1.33093	36.86253	80	1648.3	NE	83	5/16/2018 9:05	1526447128	0.8	22.22	-0.28	1	-0.1	3	-0.09
237	D1	-1.33086	36.86313	79	1647.6	NE	83	5/16/2018 9:05	1526447131	0.8	21.94	-0.28	0	-0.7	3	-0.09
238	D1	-1.33078	36.86369	73	1646.9	NE	82	5/16/2018 9:05	1526447134	0.9	20.28	-1.66	-1	-0.7	3	-0.55
239	D1	-1.33071	36.86417	63	1646.1	NE	83	5/16/2018 9:05	1526447137	0.8	17.5	-2.78	1	-0.8	3	-0.93
240	D1	-1.33062	36.86476	59	1645.6	NE	83	5/16/2018 9:05	1526447141	0.8	16.39	-1.11	0	-0.5	4	-0.28
241	D1	-1.33053	36.8653	51	1647.2	NE	81	5/16/2018 9:05	1526447145	0.8	14.17	-2.22	-2	1.6	4	-0.56
242	D1	-1.33046	36.86584	43	1648.3	NE	85	5/16/2018 9:05	1526447150	0.9	11.94	-2.23	4	1.1	5	-0.45
243	D1	-1.33042	36.86617	45	1649.3	NE	83	5/16/2018 9:05	1526447153	0.9	12.5	0.56	-2	1	3	0.19
244	D1	-1.33019	36.86773	57	1649.6	NE	82	5/16/2018 9:06	1526447166	0.9	15.83	3.33	-1	0.3	13	0.26
245	D1	-1.33013	36.86819	61	1653.8	NE	83	5/16/2018 9:06	1526447169	0.8	16.94	1.11	1	4.2	3	0.37
246	D1	-1.32999	36.86918	68	1649.1	NE	83	5/16/2018 9:06	1526447175	0.8	18.89	1.95	0	-4.7	6	0.33
247	D1	-1.32984	36.87027	77	1646.5	NE	82	5/16/2018 9:06	1526447181	0.8	21.39	2.5	-1	-2.6	6	0.42

248	D1	-1.32971	36.87146	80	1643.2	NE	83	5/16/2018 9:06	1526447187	0.8	22.22	0.83	1	-3.3	6	0.14
249	D1	-1.32937	36.87386	80	1644.3	NE	82	5/16/2018 9:06	1526447199	0.8	22.22	0	-1	1.1	12	0
250	D1	-1.32928	36.87445	81	1646.1	NE	82	5/16/2018 9:06	1526447202	0.8	22.5	0.28	0	1.8	3	0.09
251	D1	-1.32921	36.87506	81	1647.4	NE	83	5/16/2018 9:06	1526447205	0.8	22.5	0	1	1.3	3	0
252	D1	-1.32913	36.87567	83	1647.8	NE	82	5/16/2018 9:06	1526447208	0.8	23.06	0.56	-1	0.4	3	0.19
253	D1	-1.32904	36.87629	84	1647.9	NE	82	5/16/2018 9:06	1526447211	0.8	23.33	0.27	0	0.1	3	0.09
254	D1	-1.3285	36.8804	84	1638.9	NE	84	5/16/2018 9:07	1526447230	0.8	23.33	0	2	-9	19	0
255	D1	-1.32848	36.88213	68	1636.5	SE	94	5/16/2018 9:07	1526447239	0.8	18.89	-4.44	10	-2.4	9	-0.49
256	D1	-1.32854	36.88273	62	1637.7	SE	98	5/16/2018 9:07	1526447243	0.8	17.22	-1.67	4	1.2	4	-0.42
257	D1	-1.32874	36.8837	70	1639.8	SE	104	5/16/2018 9:07	1526447249	0.8	19.44	2.22	6	2.1	6	0.37
258	D1	-1.32889	36.88424	75	1640.7	SE	107	5/16/2018 9:07	1526447252	0.8	20.83	1.39	3	0.9	3	0.46
259	D1	-1.32911	36.88477	78	1642	SE	113	5/16/2018 9:07	1526447255	0.8	21.67	0.84	6	1.3	3	0.28
260	D1	-1.32936	36.88532	81	1643.7	SE	115	5/16/2018 9:07	1526447258	0.8	22.5	0.83	2	1.7	3	0.28
261	D1	-1.32965	36.88587	83	1647.1	SE	119	5/16/2018 9:07	1526447261	0.8	23.06	0.56	4	3.4	3	0.19
262	D1	-1.32998	36.88641	85	1648.7	SE	122	5/16/2018 9:07	1526447264	0.8	23.61	0.55	3	1.6	3	0.18
263	D1	-1.33105	36.88774	86	1650.2	SE	130	5/16/2018 9:07	1526447272	0.8	23.89	0.28	8	1.5	8	0.04
264	D1	-1.33363	36.89069	74	1644.9	SE	131	5/16/2018 9:08	1526447291	0.8	20.56	-3.33	1	-5.3	19	-0.18
265	D1	-1.33395	36.89107	67	1644.9	SE	131	5/16/2018 9:08	1526447294	0.8	18.61	-1.95	0	0	3	-0.65
266	D1	-1.33428	36.89143	65	1644.4	SE	132	5/16/2018 9:08	1526447297	0.9	18.06	-0.55	1	-0.5	3	-0.18
267	D1	-1.33465	36.89187	56	1644.1	SE	132	5/16/2018 9:08	1526447301	0.8	15.56	-2.5	0	-0.3	4	-0.63
268	D1	-1.33504	36.8923	61	1643.6	SE	132	5/16/2018 9:08	1526447305	0.8	16.94	1.38	0	-0.5	4	0.35
269	D1	-1.33544	36.89275	59	1642.3	SE	131	5/16/2018 9:08	1526447309	0.8	16.39	-0.55	-1	-1.3	4	-0.14
270	D1	-1.3358	36.89316	52	1642.7	SE	131	5/16/2018 9:08	1526447313	0.8	14.44	-1.95	0	0.4	4	-0.49
271	D1	-1.33612	36.89353	49	1642.5	SE	129	5/16/2018 9:08	1526447317	0.8	13.61	-0.83	-2	-0.2	4	-0.21
272	D1	-1.33645	36.89394	53	1641	SE	130	5/16/2018 9:08	1526447321	0.8	14.72	1.11	1	-1.5	4	0.28
273	D1	-1.33682	36.89436	52	1639.7	SE	132	5/16/2018 9:08	1526447325	0.8	14.44	-0.28	2	-1.3	4	-0.07
274	D1	-1.33714	36.89472	48	1640.2	SE	131	5/16/2018 9:08	1526447329	0.8	13.33	-1.11	-1	0.5	4	-0.28
275	D1	-1.33748	36.8951	55	1640.5	SE	133	5/16/2018 9:08	1526447333	0.8	15.28	1.95	2	0.3	4	0.49
276	D1	-1.33901	36.89682	72	1640.7	SE	131	5/16/2018 9:09	1526447347	0.8	20	4.72	-2	0.2	14	0.34
277	D1	-1.33937	36.89723	75	1641	SE	131	5/16/2018 9:09	1526447350	0.8	20.83	0.83	0	0.3	3	0.28
278	D1	-1.33976	36.89766	77	1641.4	SE	131	5/16/2018 9:09	1526447353	0.8	21.39	0.56	0	0.4	3	0.19
279	D1	-1.34012	36.89807	69	1641.9	SE	131	5/16/2018 9:09	1526447356	0.8	19.17	-2.22	0	0.5	3	-0.74
280	D1	-1.34042	36.89845	63	1641.3	SE	128	5/16/2018 9:09	1526447359	0.8	17.5	-1.67	-3	-0.6	3	-0.56
281	D1	-1.34074	36.89882	66	1640.6	SE	131	5/16/2018 9:09	1526447362	0.8	18.33	0.83	3	-0.7	3	0.28
282	D1	-1.34107	36.8992	69	1641.2	SE	131	5/16/2018 9:09	1526447365	0.8	19.17	0.84	0	0.6	3	0.28
283	D1	-1.34143	36.8996	73	1642.2	SE	131	5/16/2018 9:09	1526447368	0.8	20.28	1.11	0	1	3	0.37
284	D1	-1.34181	36.90002	77	1642.8	SE	131	5/16/2018 9:09	1526447371	0.8	21.39	1.11	0	0.6	3	0.37
285	D1	-1.34221	36.90048	81	1643.5	SE	131	5/16/2018 9:09	1526447374	0.8	22.5	1.11	0	0.7	3	0.37
286	D1	-1.34264	36.90094	87	1644.9	SE	134	5/16/2018 9:09	1526447377	0.8	24.17	1.67	3	1.4	3	0.56
287	D1	-1.34386	36.90235	92	1644.8	SE	130	5/16/2018 9:09	1526447385	0.8	25.56	1.39	-4	-0.1	8	0.17
288	D1	-1.34416	36.90271	91	1644.6	SE	130	5/16/2018 9:09	1526447387	0.8	25.28	-0.28	0	-0.2	2	-0.14
289	D1	-1.34445	36.90305	91	1644.6	SE	131	5/16/2018 9:09	1526447389	0.8	25.28	0	1	0	2	0
290	D1	-1.34475	36.90339	90	1644.9	SE	132	5/16/2018 9:09	1526447391	0.8	25	-0.28	1	0.3	2	-0.14
291	D1	-1.34606	36.9068	64	1639.3	NE	84	5/16/2018 9:10	1526447411	0.8	17.78	-7.22	-48	-5.6	20	-0.36
292	D1	-1.34602	36.90733	49	1637.6	NE	88	5/16/2018 9:10	1526447415	0.8	13.61	-4.17	4	-1.7	4	-1.04
293	D1	-1.34594	36.90783	42	1637.1	NE	75	5/16/2018 9:10	1526447420	0.8	11.67	-1.94	-13	-0.5	5	-0.39
294	D1	-1.34586	36.9083	13	1632.4	SE	92	5/16/2018 9:10	1526447439	0.8	3.61	-8.06	17	-4.7	19	-0.42
295	D1	-1.34608	36.90879	35	1629.9	SE	126	5/16/2018 9:11	1526447511	0.8	9.72	6.11	34	-2.5	72	0.08
296	D1	-1.34658	36.91	41	1635.5	NE	82	5/16/2018 9:12	1526447526	0.9	11.39	1.67	-44	5.6	15	0.11
297	D1	-1.34647	36.91049	57	1634.1	NE	73	5/16/2018 9:12	1526447530	0.8	15.83	4.44	-9	-1.4	4	1.11
298	D1	-1.34628	36.91097	71	1633.7	NE	69	5/16/2018 9:12	1526447533	0.8	19.72	3.89	-4	-0.4	3	1.3
299	D1	-1.34605	36.91151	80	1633.2	NE	65	5/16/2018 9:12	1526447536	0.8	22.22	2.5	-4	-0.5	3	0.83
300	D1	-1.34575	36.91207	87	1632.8	NE	60	5/16/2018 9:12	1526447539	0.8	24.17	1.95	-5	-0.4	3	0.65
301	D1	-1.34467	36.91358	85	1631.4	NE	53	5/16/2018 9:12	1526447547	0.8	23.61	-0.56	-7	-1.4	8	-0.07
302	D1	-1.34436	36.91398	65	1630.6	NE	51	5/16/2018 9:12	1526447550	0.8	18.06	-5.55	-2	-0.8	3	-1.85
303	D1	-1.34416	36.91415	55	1630.1	NE	33	5/16/2018 9:12	1526447552	0.8	15.28	-2.78	-18	-0.5	2	-1.39
304	D1	-1.34392	36.91425	52	1629.3	NE	19	5/16/2018 9:12	1526447554	0.8	14.44	-0.84	-14	-0.8	2	-0.42
305	D1	-1.3437	36.91427	45	1628.3	N	360	5/16/2018 9:12	1526447556	0.8	12.5	-1.94	341	-1	2	-0.97
306	D1	-1.34338	36.91412	49	1627.5	NW	326	5/16/2018 9:12	1526447559	0.8	13.61	1.11	-34	-0.8	3	0.37
307	D1	-1.34293	36.91376	60	1628.2	NW	324	5/16/2018 9:12	1526447563	0.8	16.67	3.06	-2	0.7	4	0.77
308	D1	-1.34216	36.91317	65	1629	NW	324	5/16/2018 9:12	1526447569	0.8	18.06	1.39	0	0.8	6	0.23
309	D1	-1.34176	36.91288	65	1628.8	NW	324	5/16/2018 9:12	1526447572	0.8	18.06	0	0	-0.2	3	0
310	D1	-1.3403	36.91182	38	1630.4	NW	325	5/16/2018 9:13	1526447586	0.8	10.56	-7.5	1	1.6	14	-0.54
311	D1	-1.33995	36.91154	27	1631.3	NW	312	5/16/2018 9:13	1526447592	0.8	7.5	-3.06	-13	0.9	6	-0.51
312	D1	-1.3399	36.9114	32	1631.2	NW	285	5/16/2018 9:13	1526447594	0.8	8.89	1.39	-27	-0.1	2	0.7
313	D1	-1.33987	36.91105	38	1632	SW	265	5/16/2018 9:13	1526447598	0.9	10.56	1.67	-20	0.8	4	0.42
314	D1	-1.33993	36.91087	38	1632.1	SW	246	5/16/2018 9:13	1526447600	0.8	10.56	0	-19	0.1	2	0
315	D1	-1.34024	36.91046	40	1634.2	SW	233	5/16/2018 9:13	1526447605	0.8	11.11	0.55	-13	2.1	5	0.11
316	D1	-1.34053	36.91007	36	1632.9	SW	234	5/16/2018 9:13	1526447610	0.8	10	-1.11	1	-1.3	5	-0.22
317	D1	-1.34087	36.90971	31	1631.4	SW	227	5/16/2018 9:13	1526447616	0.8	8.61	-1.39	-7	-1.5	6	-0.23
318	D1	-1.34111	36.9093	22	1630.6	SW	240	5/16/2018 9:13	1526447624	0.8	6.11	-2.5	13	-0.8	8	-0.31
319	D1	-1.34146	36.90846	15	1631.2	SW	238	5/16/2018 9:14	1526447646	0.8	4.17	-1.94	-2	0.6	22	-0.09
320	D1	-1.34176	36.90806	17	1631.7	SW	231	5/16/2018 9:14	1526447658	0.8	4.72	0.55	-7	0.5	12	0.05
321	D1	-1.34194	36.90754	24	1632.1	SW	250	5/16/2018 9:14	1526447670	0.8	6.67	1.95	19	0.4	12	0.16
322	D1	-1.34207	36.90702	28	1633.9	SW	258	5/16/2018 9:14	1526447678	0.8	7.78	1.11	8	1.8	8	0.14
323	D1	-1.34221	36.90625	2	1636.7	NE	72	5/16/2018 9:16	1526447761	0.9	0.56	-7.22	-186	2.8	83	-0.09
324	D1	-1.34221	36.90625	1	1636.8	NE	78	5/16/2018 9:16	1526447764	0.9	0.28	-0.28	6	0.1	3	-0.09
325	D1	-1.34222	36.90626	2	1634.5	SW	243	5/16/2018 9:17	1526447858	0.9	0.56	0.28	165	-2.3	94	0
326	D1	-1.34225	36.90622	2	1636.1	NE	65	5/16/2018 9:18	1526447890	0.8	0.56	0	-178	1.6	32	0
327	D1	-1.34221	36.90624	2	1640.4	SW	251	5/16/2018 9:24	1526448281	0.9	0.56	0	186	4.3	391	0
328	D1	-1.34228	36.90607	4	1637.2	NW	296	5/16/2018 9:26	1526448363	0.9	1.11	0.55	45	-3.2	82	0.01
329	D1	-1.34228	36.90605	4	1637.2	NW	300	5/16/2018 9:26	1526448365	0.8	1.11	0	4	0	2	0
330	D1	-1.34219	36.90588	9	1643.3	NW	288	5/16/2018 9:26	1526448374	0.8	2.5	1.39	-12	6.1	9	0.15
331	D1	-1.34204	36.90527	4	1651.1	SW	234	5/16/2018 9:26	1526448408	0.8	1.11	-1.39	-54	7.8	34	-0.04

332	D1	-1.34205	36.90525	4	1649.9	SW	202	5/16/2018 9:26	1526448410	0.8	1.11	0	-32	-1.2	2	0
333	D1	-1.34207	36.90525	4	1647.5	SW	186	5/16/2018 9:26	1526448412	0.8	1.11	0	-16	-2.4	2	0
334	D1	-1.34236	36.90512	4	1638.9	SW	231	5/16/2018 9:27	1526448437	0.8	1.11	0	45	-8.6	25	0
335	D1	-1.3424	36.90511	3	1637.1	SE	177	5/16/2018 9:27	1526448443	0.8	0.83	-0.28	-54	-1.8	6	-0.05
336	D1	-1.34235	36.90509	0	1655.3	SE	158	5/16/2018 9:36	1526448967	0.8	0	-0.83	-19	18.2	524	0
337	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 9:46	1526449568	0.7	0	0	0	-16.1	601	0
338	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 9:56	1526450169	0.8	0	0	0	0	601	0
339	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 10:06	1526450770	0.7	0	0	0	0	601	0
340	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 10:16	1526451372	0.8	0	0	0	0	602	0
341	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 10:26	1526451973	0.8	0	0	0	0	601	0
342	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 10:36	1526452574	0.8	0	0	0	0	601	0
343	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 10:46	1526453175	0.9	0	0	0	0	601	0
344	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 10:56	1526453777	0.8	0	0	0	0	602	0
345	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 11:06	1526454378	0.8	0	0	0	0	601	0
346	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 11:16	1526454979	0.8	0	0	0	0	601	0
347	D1	-1.34238	36.90511	0	1639.2	SE	158	5/16/2018 11:26	1526455580	0.8	0	0	0	0	601	0
348	D1	-1.34242	36.90509	2	1639.9	NE	36	5/16/2018 11:28	1526455684	0.8	0.56	0.56	-122	0.7	104	0.01
349	D1	-1.34242	36.90509	5	1639.9	SW	229	5/16/2018 11:28	1526455689	0.8	1.39	0.83	193	0	5	0.17
350	D1	-1.34261	36.90493	5	1637.7	SE	144	5/16/2018 11:28	1526455703	0.8	1.39	0	-85	-2.2	14	0
351	D1	-1.34259	36.90494	2	1636.5	NW	319	5/16/2018 11:28	1526455708	0.8	0.56	-0.83	175	-1.2	5	-0.17
352	D1	-1.34255	36.90488	3	1633.3	SE	109	5/16/2018 11:28	1526455721	0.8	0.83	0.27	-210	-3.2	13	0.02
353	D1	-1.34255	36.90488	2	1631.3	NW	301	5/16/2018 11:28	1526455725	0.8	0.56	-0.27	192	-2	4	-0.07
354	D1	-1.34255	36.90486	3	1629.6	SE	96	5/16/2018 11:28	1526455735	0.8	0.83	0.27	-205	-1.7	10	0.03
355	D1	-1.34254	36.90487	6	1629.6	NE	50	5/16/2018 11:28	1526455737	0.9	1.67	0.84	-46	0	2	0.42
356	D1	-1.34204	36.90527	13	1636.4	NE	73	5/16/2018 11:29	1526455763	0.8	3.61	1.94	23	6.8	26	0.07
357	D1	-1.34204	36.90535	15	1636.4	SE	99	5/16/2018 11:29	1526455765	0.8	4.17	0.56	26	0	2	0.28
358	D1	-1.34217	36.90578	7	1627.6	SE	117	5/16/2018 11:29	1526455782	0.9	1.94	-2.23	18	-8.8	17	-0.13
359	D1	-1.34205	36.90683	21	1631.4	NE	78	5/16/2018 11:30	1526455823	0.8	5.83	3.89	-39	3.8	41	0.09
360	D1	-1.34194	36.90737	26	1634	NE	77	5/16/2018 11:30	1526455832	0.8	7.22	1.39	-1	2.6	9	0.15
361	D1	-1.3418	36.90789	26	1629.8	NE	74	5/16/2018 11:30	1526455840	0.9	7.22	0	-3	-4.2	8	0
362	D1	-1.34171	36.90809	21	1628.6	NE	52	5/16/2018 11:30	1526455844	0.8	5.83	-1.39	-22	-1.2	4	-0.35
363	D1	-1.34154	36.90832	18	1629.4	NE	54	5/16/2018 11:30	1526455851	0.8	5	-0.83	2	0.8	7	-0.12
364	D1	-1.34129	36.90875	19	1629.8	NE	67	5/16/2018 11:31	1526455862	0.8	5.28	0.28	13	0.4	11	0.03
365	D1	-1.34099	36.90955	19	1626.7	NE	73	5/16/2018 11:31	1526455883	0.8	5.28	0	6	-3.1	21	0
366	D1	-1.33929	36.9113	35	1632.7	NE	59	5/16/2018 11:31	1526455914	0.8	9.72	4.44	-14	6	31	0.14
367	D1	-1.33929	36.91155	35	1630.5	SE	111	5/16/2018 11:31	1526455917	0.8	9.72	0	52	-2.2	3	0
368	D1	-1.33951	36.91171	37	1629.5	SE	162	5/16/2018 11:32	1526455920	0.8	10.28	0.56	51	-1	3	0.19
369	D1	-1.34007	36.9118	46	1629.8	SE	164	5/16/2018 11:32	1526455925	0.8	12.78	2.5	2	0.3	5	0.5
370	D1	-1.34051	36.91204	50	1628.1	SE	148	5/16/2018 11:32	1526455929	0.8	13.89	1.11	-16	-1.7	4	0.28
371	D1	-1.3421	36.91316	57	1624.7	SE	144	5/16/2018 11:32	1526455943	0.8	15.83	1.94	-4	-3.4	14	0.14
372	D1	-1.34305	36.91384	57	1623.9	SE	144	5/16/2018 11:32	1526455951	0.8	15.83	0	0	-0.8	8	0
373	D1	-1.34347	36.91415	50	1623.8	SE	143	5/16/2018 11:32	1526455955	0.8	13.89	-1.94	-1	-0.1	4	-0.49
374	D1	-1.34364	36.91439	40	1624.2	SE	110	5/16/2018 11:32	1526455958	0.8	11.11	-2.78	-33	0.4	3	-0.93
375	D1	-1.34366	36.91459	42	1624.2	SE	93	5/16/2018 11:32	1526455960	0.8	11.67	0.56	-17	0	2	0.28
376	D1	-1.34368	36.91515	45	1625.1	SE	112	5/16/2018 11:32	1526455965	0.8	12.5	0.83	19	0.9	5	0.17
377	D1	-1.34384	36.91529	43	1625	SE	156	5/16/2018 11:32	1526455967	0.8	11.94	-0.56	44	-0.1	2	-0.28
378	D1	-1.34415	36.91525	44	1625.2	SW	201	5/16/2018 11:32	1526455970	0.8	12.22	0.28	45	0.2	3	0.09
379	D1	-1.34451	36.91493	49	1625.8	SW	234	5/16/2018 11:32	1526455974	0.8	13.61	1.39	33	0.6	4	0.35
380	D1	-1.34462	36.91469	50	1626	SW	252	5/16/2018 11:32	1526455976	0.8	13.89	0.28	18	0.2	2	0.14
381	D1	-1.34468	36.91444	51	1625.5	SW	254	5/16/2018 11:32	1526455978	0.8	14.17	0.28	2	-0.5	2	0.14
382	D1	-1.34496	36.91396	59	1625.3	SW	233	5/16/2018 11:33	1526455982	0.8	16.39	2.22	-21	-0.2	4	0.56
383	D1	-1.34524	36.91358	64	1625.1	SW	234	5/16/2018 11:33	1526455985	0.8	17.78	1.39	1	-0.2	3	0.46
384	D1	-1.34554	36.91317	68	1624.6	SW	234	5/16/2018 11:33	1526455988	0.8	18.89	1.11	0	-0.5	3	0.37
385	D1	-1.34584	36.91273	71	1624.2	SW	236	5/16/2018 11:33	1526455991	0.8	19.72	0.83	2	-0.4	3	0.28
386	D1	-1.34735	36.91057	78	1627.3	SW	238	5/16/2018 11:33	1526456005	0.8	21.67	1.95	2	3.1	14	0.14
387	D1	-1.34763	36.91005	79	1628.7	SW	244	5/16/2018 11:33	1526456008	0.8	21.94	0.27	6	1.4	3	0.09
388	D1	-1.34786	36.90949	79	1630.4	SW	249	5/16/2018 11:33	1526456011	0.8	21.94	0	5	1.7	3	0
389	D1	-1.34804	36.90892	80	1630.7	SW	254	5/16/2018 11:33	1526456014	0.8	22.22	0.28	5	0.3	3	0.09
390	D1	-1.34818	36.90834	81	1630.7	SW	259	5/16/2018 11:33	1526456017	0.8	22.5	0.28	5	0	3	0.09
391	D1	-1.34826	36.90773	82	1631	SW	263	5/16/2018 11:33	1526456020	0.8	22.78	0.28	4	0.3	3	0.09
392	D1	-1.34829	36.9071	84	1632.2	SW	269	5/16/2018 11:33	1526456023	0.8	23.33	0.55	6	1.2	3	0.18
393	D1	-1.34808	36.90537	90	1633.4	NW	283	5/16/2018 11:33	1526456031	0.8	25	1.67	14	1.2	8	0.21
394	D1	-1.34762	36.90407	92	1632.7	NW	293	5/16/2018 11:33	1526456037	0.8	25.56	0.56	10	-0.7	6	0.09
395	D1	-1.34741	36.90366	91	1632.2	NW	297	5/16/2018 11:33	1526456039	0.8	25.28	-0.28	4	-0.5	2	-0.14
396	D1	-1.34719	36.90327	89	1631.5	NW	301	5/16/2018 11:34	1526456041	0.8	24.72	-0.56	4	-0.7	2	-0.28
397	D1	-1.3468	36.90273	87	1631.3	NW	306	5/16/2018 11:34	1526456044	0.8	24.17	-0.55	5	-0.2	3	-0.18
398	D1	-1.34592	36.9018	85	1632.1	NW	317	5/16/2018 11:34	1526456050	0.8	23.61	-0.56	11	0.8	6	-0.09
399	D1	-1.34353	36.89961	76	1633.3	NW	315	5/16/2018 11:34	1526456067	0.8	21.11	-2.5	-2	1.2	17	-0.15
400	D1	-1.34311	36.89921	79	1632.7	NW	317	5/16/2018 11:34	1526456070	0.8	21.94	0.83	2	-0.6	3	0.28
401	D1	-1.34265	36.89882	81	1632.1	NW	319	5/16/2018 11:34	1526456073	0.8	22.5	0.56	2	-0.6	3	0.19
402	D1	-1.34218	36.8984	85	1631.8	NW	318	5/16/2018 11:34	1526456076	0.8	23.61	1.11	-1	-0.3	3	0.37
403	D1	-1.34087	36.89725	85	1632.2	NW	319	5/16/2018 11:34	1526456084	0.8	23.61	0	1	0.4	8	0
404	D1	-1.34041	36.89684	82	1632.2	NW	318	5/16/2018 11:34	1526456087	0.8	22.78	-0.83	-1	0	3	-0.28
405	D1	-1.33997	36.89644	80	1631.9	NW	318	5/16/2018 11:34	1526456090	0.8	22.22	-0.56	0	-0.3	3	-0.19
406	D1	-1.33953	36.89604	79	1631.6	NW	317	5/16/2018 11:34	1526456093	0.8	21.94	-0.28	-1	-0.3	3	-0.09
407	D1	-1.3387	36.89527	74	1630.7	NW	317	5/16/2018 11:34	1526456099	0.8	20.56	-1.38	0	-0.9	6	-0.23
408	D1	-1.33831	36.8949	72	1630.7	NW	316	5/16/2018 11:35	1526456102	0.8	20	-0.56	-1	0	3	-0.19
409	D1	-1.33793	36.89455	68	1630.8	NW	317	5/16/2018 11:35	1526456105	0.8	18.89	-1.11	1	0.1	3	-0.37
410	D1	-1.33757	36.89421	66	1631	NW	316	5/16/2018 11:35	1526456108	0.8	18.33	-0.56	-1	0.2	3	-0.19
411	D1	-1.33722	36.89387	66	1630.8	NW	315	5/16/2018 11:35	1526456111	0.8	18.33	0	-1	-0.2	3	0
412	D1	-1.33548	36.89213	75	1632.8	NW	314	5/16/2018 11:35	1526456125	0.8	20.83	2.5	-1	2	14	0.18
413	D1	-1.33508	36.89171	78	1632.9	NW	314	5/16/2018 11:35	1526456128	0.8	21.67	0.84	0	0.1	3	0.28
414	D1	-1.33468	36.89129	75	1632.8	NW	314	5/16/2018 11:35	1526456131	0.8	20.83	-0.84	0	-0.1	3	-0.28
415	D1	-1.33431	36.8909	70	1632.7	NW	313	5/16/2018 11:35	1526456134	0.8	19.44	-1.39	-1	-0.1	3	-0.46

416	D1	-1.33397	36.89053	66	1632.8	NW	313	5/16/2018 11:35	1526456137	0.8	18.33	-1.11	0	0.1	3	-0.37
417	D1	-1.33365	36.89018	63	1633	NW	312	5/16/2018 11:35	1526456140	0.8	17.5	-0.83	-1	0.2	3	-0.28
418	D1	-1.33334	36.88983	62	1633.3	NW	312	5/16/2018 11:35	1526456143	0.8	17.22	-0.28	0	0.3	3	-0.09
419	D1	-1.33302	36.88949	63	1633.3	NW	312	5/16/2018 11:35	1526456146	0.8	17.5	0.28	0	0	3	0.09
420	D1	-1.33263	36.88904	58	1633.6	NW	311	5/16/2018 11:35	1526456150	0.8	16.11	-1.39	-1	0.3	4	-0.35
421	D1	-1.33223	36.88859	64	1634.2	NW	312	5/16/2018 11:35	1526456154	0.8	17.78	1.67	1	0.6	4	0.42
422	D1	-1.3319	36.88821	67	1634.6	NW	312	5/16/2018 11:35	1526456157	0.8	18.61	0.83	0	0.4	3	0.28
423	D1	-1.33155	36.88783	70	1635	NW	312	5/16/2018 11:36	1526456160	0.8	19.44	0.83	0	0.4	3	0.28
424	D1	-1.33119	36.88744	71	1634.9	NW	312	5/16/2018 11:36	1526456163	0.8	19.72	0.28	0	-0.1	3	0.09
425	D1	-1.33084	36.88703	71	1634.9	NW	310	5/16/2018 11:36	1526456166	0.8	19.72	0	-2	0	3	0
426	D1	-1.33052	36.88661	47	1634.6	NW	305	5/16/2018 11:36	1526456170	0.8	13.06	-6.66	-5	-0.3	4	-1.67
427	D1	-1.33042	36.88648	34	1634.7	NW	304	5/16/2018 11:36	1526456172	0.8	9.44	-3.62	-1	0.1	2	-1.81
428	D1	-1.32997	36.88578	15	1635.4	NW	310	5/16/2018 11:36	1526456217	0.8	4.17	-5.27	6	0.7	45	-0.12
429	D1	-1.32974	36.88535	22	1635.3	NW	296	5/16/2018 11:37	1526456225	0.8	6.11	1.94	-14	-0.1	8	0.24
430	D1	-1.32943	36.88475	16	1636.7	NW	293	5/16/2018 11:37	1526456244	0.8	4.44	-1.67	-3	1.4	19	-0.09
431	D1	-1.32925	36.88428	14	1638.7	NW	289	5/16/2018 11:37	1526456255	0.8	3.89	-0.55	-4	2	11	-0.05
432	D1	-1.3291	36.88382	20	1640.6	NW	286	5/16/2018 11:37	1526456266	0.8	5.56	1.67	-3	1.9	11	0.15
433	D1	-1.32896	36.88325	16	1632.5	NW	283	5/16/2018 11:38	1526456286	0.8	4.44	-1.12	-3	-8.1	20	-0.06
434	D1	-1.32882	36.88224	28	1632.1	NW	276	5/16/2018 11:38	1526456304	0.8	7.78	3.34	-7	-0.4	18	0.19
435	D1	-1.3288	36.88177	33	1632.3	NW	274	5/16/2018 11:38	1526456310	0.8	9.17	1.39	-2	0.2	6	0.23
436	D1	-1.32879	36.88131	37	1632.2	W	270	5/16/2018 11:38	1526456315	0.8	10.28	1.11	-4	-0.1	5	0.22
437	D1	-1.32881	36.88075	39	1632.6	SW	266	5/16/2018 11:38	1526456321	0.8	10.83	0.55	-4	0.4	6	0.09
438	D1	-1.32885	36.88022	43	1634.2	SW	264	5/16/2018 11:38	1526456326	0.8	11.94	1.11	-2	1.6	5	0.22
439	D1	-1.32892	36.87967	45	1636	SW	262	5/16/2018 11:38	1526456331	0.8	12.5	0.56	-2	1.8	5	0.11
440	D1	-1.32897	36.87922	46	1637.3	SW	263	5/16/2018 11:38	1526456335	0.8	12.78	0.28	1	1.3	4	0.07
441	D1	-1.32904	36.87875	49	1638	SW	262	5/16/2018 11:38	1526456339	0.8	13.61	0.83	-1	0.7	4	0.21
442	D1	-1.32911	36.87823	53	1638.4	SW	262	5/16/2018 11:39	1526456343	0.8	14.72	1.11	0	0.4	4	0.28
443	D1	-1.32918	36.87773	48	1638.5	SW	262	5/16/2018 11:39	1526456347	0.8	13.33	-1.39	0	0.1	4	-0.35
444	D1	-1.32925	36.87724	50	1639.7	SW	262	5/16/2018 11:39	1526456351	0.8	13.89	0.56	0	1.2	4	0.14
445	D1	-1.32943	36.87565	45	1642.2	SW	263	5/16/2018 11:39	1526456365	0.8	12.5	-1.39	1	2.5	14	-0.1
446	D1	-1.3295	36.87515	36	1642.4	SW	262	5/16/2018 11:39	1526456370	0.9	10	-2.5	-1	0.2	5	-0.5
447	D1	-1.32957	36.87469	28	1642.8	SW	257	5/16/2018 11:39	1526456377	0.8	7.78	-2.22	-5	0.4	7	-0.32
448	D1	-1.32966	36.87418	22	1643.1	SW	264	5/16/2018 11:39	1526456385	0.8	6.11	-1.67	7	0.3	8	-0.21
449	D1	-1.32973	36.87368	23	1642.6	SW	263	5/16/2018 11:39	1526456399	0.8	6.39	0.28	-1	-0.5	14	0.02
450	D1	-1.3298	36.87317	24	1640.4	SW	263	5/16/2018 11:40	1526456407	0.8	6.67	0.28	0	-2.2	8	0.04
451	D1	-1.32993	36.87223	19	1638	SW	263	5/16/2018 11:40	1526456425	0.8	5.28	-1.39	0	-2.4	18	-0.08
452	D1	-1.32999	36.87171	18	1638.6	SW	264	5/16/2018 11:40	1526456439	0.8	5	-0.28	1	0.6	14	-0.02
453	D1	-1.33006	36.87116	17	1640.8	SW	261	5/16/2018 11:40	1526456458	0.8	4.72	-0.28	-3	2.2	19	-0.01
454	D1	-1.33015	36.87063	28	1640.7	SW	262	5/16/2018 11:41	1526456467	0.8	7.78	3.06	1	-0.1	9	0.34
455	D1	-1.3304	36.86894	46	1639.6	SW	262	5/16/2018 11:41	1526456484	0.8	12.78	5	0	-1.1	17	0.29
456	D1	-1.33047	36.86842	33	1639.9	SW	263	5/16/2018 11:41	1526456489	0.8	9.17	-3.61	1	0.3	5	-0.72
457	D1	-1.33054	36.86792	26	1638.8	SW	262	5/16/2018 11:41	1526456500	0.8	7.22	-1.95	-1	-1.1	11	-0.18
458	D1	-1.33061	36.8674	34	1639	SW	262	5/16/2018 11:41	1526456507	0.9	9.44	2.22	0	0.2	7	0.32
459	D1	-1.33068	36.86694	40	1638.8	SW	264	5/16/2018 11:41	1526456512	0.9	11.11	1.67	2	-0.2	5	0.33
460	D1	-1.33074	36.86641	44	1639.5	SW	265	5/16/2018 11:41	1526456517	0.8	12.22	1.11	1	0.7	5	0.22
461	D1	-1.33086	36.86541	48	1639.7	SW	262	5/16/2018 11:42	1526456526	0.8	13.33	1.11	-3	0.2	9	0.12
462	D1	-1.33093	36.86488	39	1640.6	SW	262	5/16/2018 11:42	1526456531	0.8	10.83	-2.5	0	0.9	5	-0.5
463	D1	-1.33114	36.8634	47	1640.6	SW	263	5/16/2018 11:42	1526456545	0.8	13.06	2.23	1	0	14	0.16
464	D1	-1.33121	36.86289	55	1641.3	SW	263	5/16/2018 11:42	1526456549	1	15.28	2.22	0	0.7	4	0.56
465	D1	-1.3313	36.8623	60	1641.9	SW	262	5/16/2018 11:42	1526456553	0.8	16.67	1.39	-1	0.6	4	0.35
466	D1	-1.33136	36.86184	61	1642.6	SW	262	5/16/2018 11:42	1526456556	0.8	16.94	0.27	0	0.7	3	0.09
467	D1	-1.33141	36.86138	64	1643.2	SW	264	5/16/2018 11:42	1526456559	0.8	17.78	0.84	2	0.6	3	0.28
468	D1	-1.33142	36.86089	68	1643.7	SW	269	5/16/2018 11:42	1526456562	0.8	18.89	1.11	5	0.5	3	0.37
469	D1	-1.33144	36.86038	68	1643.9	SW	269	5/16/2018 11:42	1526456565	0.8	18.89	0	0	0.2	3	0
470	D1	-1.33142	36.85988	67	1644	NW	273	5/16/2018 11:42	1526456568	0.8	18.61	-0.28	4	0.1	3	-0.09
471	D1	-1.33138	36.85937	68	1644.1	NW	277	5/16/2018 11:42	1526456571	0.8	18.89	0.28	4	0.1	3	0.09
472	D1	-1.33131	36.85888	65	1643.5	NW	280	5/16/2018 11:42	1526456574	0.8	18.06	-0.83	3	-0.6	3	-0.28
473	D1	-1.33123	36.85842	64	1642.7	NW	281	5/16/2018 11:42	1526456577	0.8	17.78	-0.28	1	-0.8	3	-0.09
474	D1	-1.33113	36.85799	58	1643	NW	286	5/16/2018 11:43	1526456580	0.8	16.11	-1.67	5	0.3	3	-0.56
475	D1	-1.33095	36.85745	58	1643.6	NW	290	5/16/2018 11:43	1526456584	0.8	16.11	0	4	0.6	4	0
476	D1	-1.3307	36.85691	60	1643.8	NW	294	5/16/2018 11:43	1526456588	0.8	16.67	0.56	4	0.2	4	0.14
477	D1	-1.3305	36.85649	63	1644.1	NW	296	5/16/2018 11:43	1526456591	0.9	17.5	0.83	2	0.3	3	0.28
478	D1	-1.32932	36.85444	71	1640.4	NW	303	5/16/2018 11:43	1526456605	0.8	19.72	2.22	7	-3.7	14	0.16
479	D1	-1.32904	36.85399	71	1640.2	NW	301	5/16/2018 11:43	1526456608	0.8	19.72	0	-2	-0.2	3	0
480	D1	-1.32877	36.85354	69	1639.5	NW	301	5/16/2018 11:43	1526456611	0.8	19.17	-0.55	0	-0.7	3	-0.18
481	D1	-1.32851	36.85311	66	1638.6	NW	300	5/16/2018 11:43	1526456614	0.8	18.33	-0.84	-1	-0.9	3	-0.28
482	D1	-1.32827	36.8527	64	1638.1	NW	300	5/16/2018 11:43	1526456617	0.8	17.78	-0.55	0	-0.5	3	-0.18
483	D1	-1.32804	36.8523	60	1638.2	NW	300	5/16/2018 11:43	1526456620	0.8	16.67	-1.11	0	0.1	3	-0.37
484	D1	-1.32777	36.85185	49	1639.2	NW	300	5/16/2018 11:43	1526456624	0.8	13.61	-3.06	0	1	4	-0.77
485	D1	-1.32754	36.85143	50	1639.3	NW	298	5/16/2018 11:43	1526456628	0.8	13.89	0.28	-2	0.1	4	0.07
486	D1	-1.32731	36.85103	45	1639.2	NW	301	5/16/2018 11:43	1526456632	0.8	12.5	-1.39	3	-0.1	4	-0.35
487	D1	-1.32704	36.85058	32	1638.7	NW	300	5/16/2018 11:43	1526456638	1	8.89	-3.61	-1	-0.5	6	-0.6
488	D1	-1.32678	36.8501	34	1639.1	NW	301	5/16/2018 11:44	1526456645	0.8	9.44	0.55	1	0.4	7	0.08
489	D1	-1.32652	36.84966	19	1640.2	NW	300	5/16/2018 11:44	1526456653	0.8	5.28	-4.16	-1	1.1	8	-0.52
490	D1	-1.32626	36.84921	31	1643.2	NW	301	5/16/2018 11:44	1526456670	0.8	8.61	3.33	1	3	17	0.2
491	D1	-1.32606	36.84873	47	1645.5	NW	300	5/16/2018 11:44	1526456675	0.8	13.06	4.45	-1	2.3	5	0.89
492	D1	-1.32581	36.8483	51	1645.4	NW	301	5/16/2018 11:44	1526456679	0.8	14.17	1.11	1	-0.1	4	0.28
493	D1	-1.32552	36.84786	55	1645.5	NW	303	5/16/2018 11:44	1526456683	0.8	15.28	1.11	2	0.1	4	0.28
494	D1	-1.32518	36.84736	62	1645.3	NW	301	5/16/2018 11:44	1526456687	0.8	17.22	1.94	-2	-0.2	4	0.49
495	D1	-1.32493	36.84697	60	1645.2	NW	302	5/16/2018 11:44	1526456690	1.2	16.67	-0.55	1	-0.1	3	-0.18
496	D1	-1.32462	36.84646	60	1643.7	NW	300	5/16/2018 11:44	1526456694	0.8	16.67	0	-2	-1.5	4	0
497	D1	-1.32437	36.84604	67	1642.8	NW	300	5/16/2018 11:44	1526456697	0.8	18.61	1.94	0	-0.9	3	0.65
498	D1	-1.32411	36.84557	74	1642.3	NW	299	5/16/2018 11:45	1526456700	0.8	20.56	1.95	-1	-0.5	3	0.65
499	D1	-1.3235	36.84456	80	1641.9	NW	300	5/16/2018 11:45	1526456706	0.8	22.22	1.66	1	-0.4	6	0.28

500	D1	-1.3232	36.84406	78	1642	NW	300	5/16/2018 11:45	1526456709	0.8	21.67	-0.55	0	0.1	3	-0.18
501	D1	-1.32185	36.84171	62	1646.2	NW	302	5/16/2018 11:45	1526456726	0.8	17.22	-4.45	2	4.2	17	-0.26
502	D1	-1.3216	36.84131	63	1645.9	NW	302	5/16/2018 11:45	1526456729	0.8	17.5	0.28	0	-0.3	3	0.09
503	D1	-1.32135	36.84091	64	1645.3	NW	301	5/16/2018 11:45	1526456732	0.8	17.78	0.28	-1	-0.6	3	0.09
504	D1	-1.3211	36.84052	61	1644.3	NW	302	5/16/2018 11:45	1526456735	0.8	16.94	-0.84	1	-1	3	-0.28
505	D1	-1.32078	36.84	61	1643.8	NW	303	5/16/2018 11:45	1526456739	0.8	16.94	0	1	-0.5	4	0
506	D1	-1.32051	36.8396	66	1643.3	NW	303	5/16/2018 11:45	1526456742	0.8	18.33	1.39	0	-0.5	3	0.46
507	D1	-1.32024	36.83916	71	1642.4	NW	302	5/16/2018 11:45	1526456745	0.8	19.72	1.39	-1	-0.9	3	0.46
508	D1	-1.31997	36.83872	68	1642.1	NW	302	5/16/2018 11:45	1526456748	0.8	18.89	-0.83	0	-0.3	3	-0.28
509	D1	-1.31972	36.83833	62	1642.3	NW	302	5/16/2018 11:45	1526456751	0.8	17.22	-1.67	0	0.2	3	-0.56
510	D1	-1.31941	36.83783	58	1643.1	NW	300	5/16/2018 11:45	1526456755	0.8	16.11	-1.11	-2	0.8	4	-0.28
511	D1	-1.31911	36.83734	59	1643.8	NW	301	5/16/2018 11:45	1526456759	0.8	16.39	0.28	1	0.7	4	0.07
512	D1	-1.31882	36.83685	55	1645	NW	301	5/16/2018 11:46	1526456763	0.8	15.28	-1.11	0	1.2	4	-0.28
513	D1	-1.31856	36.8364	55	1646.6	NW	301	5/16/2018 11:46	1526456767	0.8	15.28	0	0	1.6	4	0
514	D1	-1.31828	36.83593	53	1648.8	NW	301	5/16/2018 11:46	1526456771	0.8	14.72	-0.56	0	2.2	4	-0.14
515	D1	-1.31814	36.8357	55	1649.3	NW	300	5/16/2018 11:46	1526456773	0.8	15.28	0.56	-1	0.5	2	0.28
516	D1	-1.31704	36.83382	69	1653.6	NW	302	5/16/2018 11:46	1526456787	0.9	19.17	3.89	2	4.3	14	0.28
517	D1	-1.31679	36.83341	63	1653.9	NW	301	5/16/2018 11:46	1526456790	0.8	17.5	-1.67	-1	0.3	3	-0.56
518	D1	-1.31653	36.83302	63	1653.7	NW	303	5/16/2018 11:46	1526456793	0.8	17.5	0	2	-0.2	3	0
519	D1	-1.31624	36.83263	67	1653.8	NW	308	5/16/2018 11:46	1526456796	0.8	18.61	1.11	5	0.1	3	0.37
520	D1	-1.31591	36.83224	68	1654.2	NW	311	5/16/2018 11:46	1526456799	0.8	18.89	0.28	3	0.4	3	0.09
521	D1	-1.31554	36.83185	72	1654.9	NW	314	5/16/2018 11:46	1526456802	0.8	20	1.11	3	0.7	3	0.37
522	D1	-1.31513	36.83146	76	1655	NW	317	5/16/2018 11:46	1526456805	0.8	21.11	1.11	3	0.1	3	0.37
523	D1	-1.31468	36.83111	76	1654.6	NW	323	5/16/2018 11:46	1526456808	0.8	21.11	0	6	-0.4	3	0
524	D1	-1.31421	36.83079	76	1654.4	NW	327	5/16/2018 11:46	1526456811	0.8	21.11	0	4	-0.2	3	0
525	D1	-1.31373	36.8305	74	1654.7	NW	331	5/16/2018 11:46	1526456814	0.8	20.56	-0.55	4	0.3	3	-0.18
526	D1	-1.31323	36.83024	76	1655.2	NW	334	5/16/2018 11:46	1526456817	0.8	21.11	0.55	3	0.5	3	0.18
527	D1	-1.31271	36.82999	75	1656.4	NW	334	5/16/2018 11:47	1526456820	0.8	20.83	-0.28	0	1.2	3	-0.09
528	D1	-1.31221	36.82976	74	1657.4	NW	335	5/16/2018 11:47	1526456823	0.8	20.56	-0.27	1	1	3	-0.09
529	D1	-1.31169	36.82952	75	1657.6	NW	335	5/16/2018 11:47	1526456826	0.8	20.83	0.27	0	0.2	3	0.09
530	D1	-1.31118	36.82928	75	1657.3	NW	336	5/16/2018 11:47	1526456829	0.8	20.83	0	1	-0.3	3	0
531	D1	-1.31067	36.82906	72	1656.7	NW	335	5/16/2018 11:47	1526456832	0.8	20	-0.83	-1	-0.6	3	-0.28
532	D1	-1.30929	36.82843	8	1656.1	NW	335	5/16/2018 11:47	1526456846	0.8	2.22	-17.78	0	-0.6	14	-1.27
533	D1	-1.30929	36.82842	2	1656.9	NE	4	5/16/2018 11:47	1526456849	0.8	0.56	-1.66	-331	0.8	3	-0.55
534	D1	-1.30929	36.82843	2	1657.8	NW	319	5/16/2018 11:47	1526456855	0.8	0.56	0	315	0.9	6	0
535	D1	-1.30911	36.82834	2	1658.9	NE	14	5/16/2018 11:47	1526456871	0.8	0.56	0	-305	1.1	16	0
536	D1	-1.3091	36.82832	2	1662.6	NW	326	5/16/2018 11:48	1526456933	0.8	0.56	0	312	3.7	62	0
537	D1	-1.30808	36.82783	14	1655.1	NW	336	5/16/2018 11:51	1526457085	0.8	3.89	3.33	10	-7.5	152	0.02
538	D1	-1.30761	36.82761	28	1655.9	NW	335	5/16/2018 11:51	1526457095	0.8	7.78	3.89	-1	0.8	10	0.39
539	D1	-1.30713	36.82739	34	1656	NW	335	5/16/2018 11:51	1526457102	0.8	9.44	1.66	0	0.1	7	0.24
540	D1	-1.30669	36.82719	29	1655.5	NW	335	5/16/2018 11:51	1526457108	0.8	8.06	-1.38	0	-0.5	6	-0.23
541	D1	-1.30624	36.82699	18	1655.9	NW	336	5/16/2018 11:51	1526457116	0.8	5	-3.06	1	0.4	8	-0.38
542	D1	-1.30548	36.82671	15	1652.4	NW	330	5/16/2018 11:52	1526457172	0.8	4.17	-0.83	-6	-3.5	56	-0.01
543	D1	-1.30513	36.82632	16	1654.3	NW	316	5/16/2018 11:53	1526457186	0.8	4.44	0.27	-14	1.9	14	0.02
544	D1	-1.30492	36.82625	15	1657.7	N	0	5/16/2018 11:53	1526457191	0.8	4.17	-0.27	-316	3.4	5	-0.05
545	D1	-1.3047	36.82626	2	1665.4	NE	52	5/16/2018 11:53	1526457208	0.8	0.56	-3.61	52	7.7	17	-0.21
546	D1	-1.30466	36.82662	22	1658.3	NE	81	5/16/2018 11:54	1526457295	0.8	6.11	5.55	29	-7.1	87	0.06
547	D1	-1.30447	36.82706	24	1658.7	NE	63	5/16/2018 11:55	1526457302	0.8	6.67	0.56	-18	0.4	7	0.08
548	D1	-1.30426	36.82736	13	1656	NW	351	5/16/2018 11:55	1526457312	0.8	3.61	-3.06	288	-2.7	10	-0.31
549	D1	-1.30387	36.82721	11	1657.8	NW	340	5/16/2018 11:55	1526457326	0.8	3.06	-0.55	-11	1.8	14	-0.04
550	D1	-1.30339	36.82696	12	1656.5	NW	336	5/16/2018 11:55	1526457343	0.8	3.33	0.27	-4	-1.3	17	0.02
551	D1	-1.30294	36.82675	14	1654.2	NW	329	5/16/2018 11:55	1526457358	0.8	3.89	0.56	-7	-2.3	15	0.04
552	D1	-1.30271	36.82666	5	1654.8	NE	21	5/16/2018 11:56	1526457372	0.8	1.39	-2.5	-308	0.6	14	-0.18
553	D1	-1.30269	36.82668	4	1654.6	NE	64	5/16/2018 11:56	1526457374	0.8	1.11	-0.28	43	-0.2	2	-0.14
554	D1	-1.30265	36.82678	2	1663.9	NE	82	5/16/2018 11:57	1526457430	0.8	0.56	-0.55	18	9.3	56	-0.01
555	D1	-1.30266	36.82679	0	1661.3	SE	115	5/16/2018 12:06	1526457985	0.9	0	-0.56	33	-2.6	555	0
556	D1	-1.3026	36.82684	0	1657.2	SE	115	5/16/2018 12:16	1526458587	0.7	0	0	0	-4.1	602	0
557	D1	-1.3026	36.82684	0	1657.2	SE	115	5/16/2018 12:26	1526459188	0.7	0	0	0	0	601	0
558	D1	-1.3026	36.82684	0	1657.2	SE	115	5/16/2018 12:36	1526459786	0.7	0	0	0	0	598	0
559	D1	-1.30263	36.82683	2	1652.2	SW	204	5/16/2018 12:38	1526459895	0.8	0.56	0.56	89	-5	109	0.01
560	D1	-1.30264	36.82682	3	1652.5	SW	251	5/16/2018 12:39	1526459940	0.8	0.83	0.27	47	0.3	45	0.01
561	D1	-1.30263	36.82678	6	1652.2	NW	302	5/16/2018 12:39	1526459945	0.8	1.67	0.84	51	-0.3	5	0.17
562	D1	-1.30236	36.82658	14	1652.7	NW	331	5/16/2018 12:39	1526459955	0.8	3.89	2.22	29	0.5	10	0.22
563	D1	-1.30188	36.8263	11	1652.1	NW	335	5/16/2018 12:39	1526459971	0.9	3.06	-0.83	4	-0.6	16	-0.05
564	D1	-1.30141	36.82608	25	1652.5	NW	336	5/16/2018 12:39	1526459983	0.8	6.94	3.88	1	0.4	12	0.32
565	D1	-1.30094	36.82583	20	1653.9	NW	326	5/16/2018 12:39	1526459992	0.8	5.56	-1.38	-10	1.4	9	-0.15
566	D1	-1.30048	36.82563	17	1652.6	NW	336	5/16/2018 12:40	1526460002	0.8	4.72	-0.84	10	-1.3	10	-0.08
567	D1	-1.3	36.82538	20	1654.8	NW	335	5/16/2018 12:40	1526460017	0.8	5.56	0.84	-1	2.2	15	0.06
568	D1	-1.29968	36.82475	4	1651.4	SW	265	5/16/2018 12:40	1526460032	0.8	1.11	-4.45	-70	-3.4	15	-0.3
569	D1	-1.29989	36.82456	24	1666.1	SW	204	5/16/2018 12:41	1526460092	0.8	6.67	5.56	-61	14.7	60	0.09
570	D1	-1.3001	36.82448	29	1666.9	SW	196	5/16/2018 12:41	1526460095	0.8	8.06	1.39	-8	0.8	3	0.46
571	D1	-1.30054	36.82455	41	1669.8	SE	157	5/16/2018 12:41	1526460100	0.8	11.39	3.33	-39	2.9	5	0.67
572	D1	-1.30075	36.82464	46	1670.7	SE	156	5/16/2018 12:41	1526460102	0.8	12.78	1.39	-1	0.9	2	0.69
573	D1	-1.30121	36.82485	50	1674.8	SE	155	5/16/2018 12:41	1526460106	0.8	13.89	1.11	-1	4.1	4	0.28
574	D1	-1.30169	36.82506	49	1675.1	SE	155	5/16/2018 12:41	1526460110	0.8	13.61	-0.28	0	0.3	4	-0.07
575	D1	-1.30216	36.82525	46	1671.3	SE	155	5/16/2018 12:41	1526460114	0.8	12.78	-0.83	0	-3.8	4	-0.21
576	D1	-1.30264	36.82547	39	1666.2	SE	155	5/16/2018 12:41	1526460119	0.8	10.83	-1.95	0	-5.1	5	-0.39
577	D1	-1.30309	36.82568	29	1660.6	SE	155	5/16/2018 12:42	1526460125	0.8	8.06	-2.77	0	-5.6	6	-0.46
578	D1	-1.30355	36.82587	18	1656.5	SE	156	5/16/2018 12:42	1526460139	0.8	5	-3.06	1	-4.1	14	-0.22
579	D1	-1.30452	36.82639	12	1655.5	SE	133	5/16/2018 12:46	1526460363	0.8	3.33	-1.67	-23	-1	224	-0.01
580	D1	-1.30495	36.82669	20	1658.7	SW	186	5/16/2018 12:46	1526460376	0.8	5.56	2.23	53	3.2	13	0.17
581	D1	-1.30505	36.82665	19	1659	SW	213	5/16/2018 12:46	1526460378	0.8	5.28	-0.28	27	0.3	2	-0.14
582	D1	-1.30612	36.82153	60	1665.1	SW	255	5/16/2018 12:47	1526460436	0.8	16.67	11.39	42	6.1	58	0.2
583	D1	-1.30629	36.82097	61	1666.4	SW	254	5/16/2018 12:47	1526460440	0.8	16.94	0.27	-1	1.3	4	0.07

584	D1	-1.30721	36.81981	32	1665	SW	210	5/16/2018 12:47	1526460454	0.8	8.89	-8.05	-44	-1.4	14	-0.58
585	D1	-1.30757	36.81945	36	1662.7	SW	209	5/16/2018 12:47	1526460460	0.8	10	1.11	-1	-2.3	6	0.19
586	D1	-1.30809	36.81924	37	1662.7	SW	201	5/16/2018 12:47	1526460466	0.8	10.28	0.28	-8	0	6	0.05
587	D1	-1.3086	36.81903	49	1663.3	SW	203	5/16/2018 12:47	1526460471	0.8	13.61	3.33	2	0.6	5	0.67
588	D1	-1.30906	36.81876	54	1663.5	SW	213	5/16/2018 12:47	1526460475	0.8	15	1.39	10	0.2	4	0.35
589	D1	-1.30953	36.81842	59	1663.9	SW	218	5/16/2018 12:47	1526460479	0.8	16.39	1.39	5	0.4	4	0.35
590	D1	-1.30989	36.81814	59	1663.2	SW	218	5/16/2018 12:48	1526460482	0.9	16.39	0	0	-0.7	3	0
591	D1	-1.31025	36.81787	61	1662.2	SW	217	5/16/2018 12:48	1526460485	0.8	16.94	0.55	-1	-1	3	0.18
592	D1	-1.31098	36.81732	61	1661.3	SW	218	5/16/2018 12:48	1526460491	0.8	16.94	0	1	-0.9	6	0
593	D1	-1.31144	36.81695	57	1661.4	SW	218	5/16/2018 12:48	1526460495	0.8	15.83	-1.11	0	0.1	4	-0.28
594	D1	-1.3119	36.81662	56	1662.3	SW	213	5/16/2018 12:48	1526460499	0.9	15.56	-0.27	-5	0.9	4	-0.07
595	D1	-1.31241	36.81621	5	1667.4	SW	219	5/16/2018 12:48	1526460513	0.8	1.39	-14.17	6	5.1	14	-1.01
596	D1	-1.31291	36.81592	31	1675.3	SW	216	5/16/2018 12:48	1526460532	0.8	8.61	7.22	-3	7.9	19	0.38
597	D1	-1.31336	36.8157	40	1675	SW	205	5/16/2018 12:48	1526460537	0.9	11.11	2.5	-11	-0.3	5	0.5
598	D1	-1.31389	36.81546	48	1675.2	SW	206	5/16/2018 12:49	1526460542	0.9	13.33	2.22	1	0.2	5	0.44
599	D1	-1.31434	36.81525	50	1677.1	SW	205	5/16/2018 12:49	1526460546	0.8	13.89	0.56	-1	1.9	4	0.14
600	D1	-1.31481	36.81501	51	1678.6	SW	207	5/16/2018 12:49	1526460550	0.8	14.17	0.28	2	1.5	4	0.07
601	D1	-1.31527	36.81474	54	1679.3	SW	214	5/16/2018 12:49	1526460554	0.8	15	0.83	7	0.7	4	0.21
602	D1	-1.3157	36.81441	53	1680.1	SW	221	5/16/2018 12:49	1526460558	0.8	14.72	-0.28	7	0.8	4	-0.07
603	D1	-1.31719	36.81289	56	1680	SW	226	5/16/2018 12:49	1526460573	0.8	15.56	0.84	5	-0.1	15	0.06
604	D1	-1.31759	36.81248	57	1680.1	SW	226	5/16/2018 12:49	1526460577	0.8	15.83	0.27	0	0.1	4	0.07
605	D1	-1.31797	36.81207	56	1679.9	SW	227	5/16/2018 12:49	1526460581	0.8	15.56	-0.27	1	-0.2	4	-0.07
606	D1	-1.31835	36.81165	56	1679.8	SW	227	5/16/2018 12:49	1526460585	0.8	15.56	0	0	-0.1	4	0
607	D1	-1.31879	36.81123	63	1680.1	SW	223	5/16/2018 12:49	1526460589	0.8	17.5	1.94	-4	0.3	4	0.49
608	D1	-1.31915	36.81091	64	1680.1	SW	222	5/16/2018 12:49	1526460592	0.8	17.78	0.28	-1	0	3	0.09
609	D1	-1.31951	36.81058	63	1680.4	SW	223	5/16/2018 12:49	1526460595	0.8	17.5	-0.28	1	0.3	3	-0.09
610	D1	-1.31986	36.81025	64	1681.2	SW	224	5/16/2018 12:49	1526460598	0.8	17.78	0.28	1	0.8	3	0.09
611	D1	-1.3202	36.80992	64	1682.5	SW	224	5/16/2018 12:50	1526460601	1	17.78	0	0	1.3	3	0
612	D1	-1.32054	36.80959	63	1683	SW	225	5/16/2018 12:50	1526460604	0.8	17.5	-0.28	1	0.5	3	-0.09
613	D1	-1.32087	36.80927	62	1683.2	SW	225	5/16/2018 12:50	1526460607	0.8	17.22	-0.28	0	0.2	3	-0.09
614	D1	-1.3212	36.80895	61	1683.8	SW	225	5/16/2018 12:50	1526460610	0.8	16.94	-0.28	0	0.6	3	-0.09
615	D1	-1.32152	36.80862	62	1684.6	SW	225	5/16/2018 12:50	1526460613	0.8	17.22	0.28	0	0.8	3	0.09
616	D1	-1.32183	36.80827	62	1685.6	SW	230	5/16/2018 12:50	1526460616	0.8	17.22	0	5	1	3	0
617	D1	-1.3221	36.80788	62	1685.9	SW	240	5/16/2018 12:50	1526460619	0.8	17.22	0	10	0.3	3	0
618	D1	-1.32262	36.80579	59	1686	SW	259	5/16/2018 12:50	1526460633	0.8	16.39	-0.83	19	0.1	14	-0.06
619	D1	-1.32271	36.80523	57	1690	SW	261	5/16/2018 12:50	1526460637	0.8	15.83	-0.56	2	4	4	-0.14
620	D1	-1.32279	36.80468	55	1689.6	SW	263	5/16/2018 12:50	1526460641	0.8	15.28	-0.55	2	-0.4	4	-0.14
621	D1	-1.32293	36.80364	50	1688.7	SW	261	5/16/2018 12:50	1526460649	0.8	13.89	-1.39	-2	-0.9	8	-0.17
622	D1	-1.32302	36.80318	47	1688.7	SW	258	5/16/2018 12:50	1526460653	0.8	13.06	-0.83	-3	0	4	-0.21
623	D1	-1.32312	36.8027	50	1688.6	SW	260	5/16/2018 12:50	1526460657	0.8	13.89	0.83	2	-0.1	4	0.21
624	D1	-1.3232	36.80221	48	1688.3	SW	260	5/16/2018 12:51	1526460661	0.8	13.33	-0.56	0	-0.3	4	-0.14
625	D1	-1.3233	36.80175	47	1688.5	SW	258	5/16/2018 12:51	1526460665	0.8	13.06	-0.27	-2	0.2	4	-0.07
626	D1	-1.3234	36.80129	49	1690	SW	257	5/16/2018 12:51	1526460669	0.8	13.61	0.55	-1	1.5	4	0.14
627	D1	-1.3235	36.80077	54	1691.4	SW	259	5/16/2018 12:51	1526460673	0.8	15	1.39	2	1.4	4	0.35
628	D1	-1.32359	36.80024	54	1691.7	SW	260	5/16/2018 12:51	1526460677	0.8	15	0	1	0.3	4	0
629	D1	-1.32369	36.79971	54	1691.7	SW	259	5/16/2018 12:51	1526460681	0.8	15	0	-1	0	4	0
630	D1	-1.32409	36.79778	51	1698.2	SW	259	5/16/2018 12:51	1526460696	0.8	14.17	-0.83	0	6.5	15	-0.06
631	D1	-1.32421	36.79728	51	1700.8	SW	256	5/16/2018 12:51	1526460700	0.8	14.17	0	-3	2.6	4	0
632	D1	-1.32438	36.79684	48	1702.6	SW	247	5/16/2018 12:51	1526460704	0.8	13.33	-0.84	-9	1.8	4	-0.21
633	D1	-1.32459	36.79641	49	1705	SW	242	5/16/2018 12:51	1526460708	0.8	13.61	0.28	-5	2.4	4	0.07
634	D1	-1.32484	36.79598	51	1707	SW	242	5/16/2018 12:51	1526460712	0.8	14.17	0.56	0	2	4	0.14
635	D1	-1.32509	36.79551	53	1709.9	SW	242	5/16/2018 12:51	1526460716	0.8	14.72	0.55	0	2.9	4	0.14
636	D1	-1.32535	36.79505	54	1713.8	SW	241	5/16/2018 12:52	1526460720	0.8	15	0.28	-1	3.9	4	0.07
637	D1	-1.32561	36.79459	52	1717.8	SW	241	5/16/2018 12:52	1526460724	0.8	14.44	-0.56	0	4	4	-0.14
638	D1	-1.32587	36.79413	53	1720.7	SW	241	5/16/2018 12:52	1526460728	0.8	14.72	0.28	0	2.9	4	0.07
639	D1	-1.32614	36.79367	55	1722.3	SW	240	5/16/2018 12:52	1526460732	0.8	15.28	0.56	-1	1.6	4	0.14
640	D1	-1.32642	36.79318	58	1723.5	SW	240	5/16/2018 12:52	1526460736	0.8	16.11	0.83	0	1.2	4	0.21
641	D1	-1.32671	36.79267	59	1725.1	SW	241	5/16/2018 12:52	1526460740	0.8	16.39	0.28	1	1.6	4	0.07
642	D1	-1.32778	36.79087	60	1733.9	SW	241	5/16/2018 12:52	1526460754	0.8	16.67	0.28	0	8.8	14	0.02
643	D1	-1.328	36.79046	61	1735.3	SW	240	5/16/2018 12:52	1526460757	0.8	16.94	0.27	-1	1.4	3	0.09
644	D1	-1.32829	36.78996	57	1737	SW	240	5/16/2018 12:52	1526460761	0.8	15.83	-1.11	0	1.7	4	-0.28
645	D1	-1.32866	36.78906	15	1737.6	NW	315	5/16/2018 12:53	1526460800	0.8	4.17	-11.66	75	0.6	39	-0.3
646	D1	-1.32859	36.78904	16	1737.8	NE	6	5/16/2018 12:53	1526460802	0.8	4.44	0.27	-309	0.2	2	0.14
647	D1	-1.32786	36.79027	61	1738.2	NE	65	5/16/2018 12:53	1526460815	0.8	16.94	12.5	59	0.4	13	0.96
648	D1	-1.32764	36.79071	67	1737	NE	63	5/16/2018 12:53	1526460818	0.8	18.61	1.67	-2	-1.2	3	0.56
649	D1	-1.32739	36.79116	70	1735.5	NE	60	5/16/2018 12:53	1526460821	0.8	19.44	0.83	-3	-1.5	3	0.28
650	D1	-1.32713	36.79163	73	1733.5	NE	61	5/16/2018 12:53	1526460824	0.8	20.28	0.84	1	-2	3	0.28
651	D1	-1.32685	36.79211	73	1731.5	NE	60	5/16/2018 12:53	1526460827	0.8	20.28	0	-1	-2	3	0
652	D1	-1.32658	36.79258	72	1729.6	NE	60	5/16/2018 12:53	1526460830	0.8	20	-0.28	0	-1.9	3	-0.09
653	D1	-1.32503	36.79319	56	1717.8	NW	309	5/16/2018 12:54	1526460845	0.8	15.56	-4.44	249	-11.8	15	-0.3
654	D1	-1.32463	36.79277	59	1714.1	NW	329	5/16/2018 12:54	1526460849	0.8	16.39	0.83	20	-3.7	4	0.21
655	D1	-1.3242	36.79266	58	1711.4	NW	354	5/16/2018 12:54	1526460852	0.8	16.11	-0.28	25	-2.7	3	-0.09
656	D1	-1.32392	36.79263	56	1710.7	NW	355	5/16/2018 12:54	1526460854	0.8	15.56	-0.55	1	-0.7	2	-0.27
657	D1	-1.32342	36.79253	50	1708.7	NW	342	5/16/2018 12:54	1526460858	0.8	13.89	-1.67	-13	-2	4	-0.42
658	D1	-1.32118	36.79106	81	1708.6	NW	324	5/16/2018 12:54	1526460874	0.8	22.5	8.61	-18	-0.1	16	0.54
659	D1	-1.32067	36.7907	85	1709	NW	324	5/16/2018 12:54	1526460877	0.8	23.61	1.11	0	0.4	3	0.37
660	D1	-1.31809	36.78799	97	1716.4	NW	298	5/16/2018 12:54	1526460893	0.8	26.94	3.33	-26	7.4	16	0.21
661	D1	-1.31789	36.78755	98	1716.2	NW	293	5/16/2018 12:54	1526460895	0.8	27.22	0.28	-5	-0.2	2	0.14
662	D1	-1.31772	36.78709	97	1716.3	NW	289	5/16/2018 12:54	1526460897	0.8	26.94	-0.28	-4	0.1	2	-0.14
663	D1	-1.31754	36.78611	98	1718.8	NW	278	5/16/2018 12:55	1526460901	0.8	27.22	0.28	-11	2.5	4	0.07
664	D1	-1.31751	36.78561	99	1719.9	NW	273	5/16/2018 12:55	1526460903	0.8	27.5	0.28	-5	1.1	2	0.14
665	D1	-1.31752	36.78511	99	1721.1	SW	268	5/16/2018 12:55	1526460905	0.8	27.5	0	-5	1.2	2	0
666	D1	-1.31758	36.78462	100	1722.5	SW	263	5/16/2018 12:55	1526460907	0.8	27.78	0.28	-5	1.4	2	0.14
667	D1	-1.31768	36.78413	100	1724.1	SW	259	5/16/2018 12:55	1526460909	0.8	27.78	0	-4	1.6	2	0

668	D1	-1.3178	36.78364	100	1725.6	SW	256	5/16/2018 12:55	1526460911	0.8	27.78	0	-3	1.5	2	0
669	D1	-1.31793	36.78315	100	1727.2	SW	256	5/16/2018 12:55	1526460913	0.8	27.78	0	0	1.6	2	0
670	D1	-1.31805	36.78267	100	1729.2	SW	258	5/16/2018 12:55	1526460915	0.8	27.78	0	2	2	2	0
671	D1	-1.31815	36.78217	101	1731	SW	260	5/16/2018 12:55	1526460917	0.9	28.06	0.28	2	1.8	2	0.14
672	D1	-1.31824	36.78167	101	1731.6	SW	260	5/16/2018 12:55	1526460919	0.8	28.06	0	0	0.6	2	0
673	D1	-1.31832	36.78117	100	1732.1	SW	262	5/16/2018 12:55	1526460921	0.8	27.78	-0.28	2	0.5	2	-0.14
674	D1	-1.31837	36.78068	100	1733.1	SW	265	5/16/2018 12:55	1526460923	0.8	27.78	0	3	1	2	0
675	D1	-1.31899	36.7704	87	1771	SW	229	5/16/2018 12:56	1526460970	0.9	24.17	-3.61	-36	37.9	47	-0.08
676	D1	-1.31933	36.7701	89	1771.7	SW	221	5/16/2018 12:56	1526460972	0.9	24.72	0.55	-8	0.7	2	0.27
677	D1	-1.31967	36.76981	90	1773.1	SW	224	5/16/2018 12:56	1526460974	0.9	25	0.28	3	1.4	2	0.14
678	D1	-1.32014	36.76932	91	1776.8	SW	228	5/16/2018 12:56	1526460977	0.9	25.28	0.28	4	3.7	3	0.09
679	D1	-1.32044	36.76898	90	1777.8	SW	229	5/16/2018 12:56	1526460979	0.9	25	-0.28	1	1	2	-0.14
680	D1	-1.32072	36.76862	91	1779.7	SW	233	5/16/2018 12:56	1526460981	0.9	25.28	0.28	4	1.9	2	0.14
681	D1	-1.32098	36.76824	92	1781.4	SW	238	5/16/2018 12:56	1526460983	0.9	25.56	0.28	5	1.7	2	0.14
682	D1	-1.3218	36.76365	104	1792.8	SW	265	5/16/2018 12:56	1526461002	0.9	28.89	3.33	27	11.4	19	0.18
683	D1	-1.32242	36.76162	109	1794.7	SW	244	5/16/2018 12:56	1526461010	0.8	30.28	1.39	-21	1.9	8	0.17
684	D1	-1.32268	36.76114	110	1794.5	SW	240	5/16/2018 12:56	1526461012	0.8	30.56	0.28	-4	-0.2	2	0.14
685	D1	-1.32298	36.76067	111	1793.8	SW	236	5/16/2018 12:56	1526461014	0.8	30.83	0.27	-4	-0.7	2	0.14
686	D1	-1.32333	36.76024	112	1793.3	SW	232	5/16/2018 12:56	1526461016	0.8	31.11	0.28	-4	-0.5	2	0.14
687	D1	-1.32369	36.75979	113	1792.4	SW	232	5/16/2018 12:56	1526461018	0.8	31.39	0.28	0	-0.9	2	0.14
688	D1	-1.32402	36.75933	114	1791.5	SW	237	5/16/2018 12:57	1526461020	0.8	31.67	0.28	5	-0.9	2	0.14
689	D1	-1.32429	36.75883	114	1790.9	SW	243	5/16/2018 12:57	1526461022	0.8	31.67	0	6	-0.6	2	0
690	D1	-1.32452	36.75831	114	1790.7	SW	249	5/16/2018 12:57	1526461024	0.8	31.67	0	6	-0.2	2	0
691	D1	-1.32468	36.75776	114	1790.7	SW	255	5/16/2018 12:57	1526461026	0.8	31.67	0	6	0	2	0
692	D1	-1.32479	36.75721	112	1791.4	SW	260	5/16/2018 12:57	1526461028	0.8	31.11	-0.56	5	0.7	2	-0.28
693	D1	-1.32487	36.75668	107	1792.5	SW	261	5/16/2018 12:57	1526461030	0.8	29.72	-1.39	1	1.1	2	-0.7
694	D1	-1.32494	36.75617	102	1793.9	SW	262	5/16/2018 12:57	1526461032	0.8	28.33	-1.39	1	1.4	2	-0.7
695	D1	-1.32501	36.75568	100	1795	SW	261	5/16/2018 12:57	1526461034	0.8	27.78	-0.55	-1	1.1	2	-0.27
696	D1	-1.32509	36.75519	100	1796.1	SW	261	5/16/2018 12:57	1526461036	0.8	27.78	0	0	1.1	2	0
697	D1	-1.32516	36.75469	101	1797	SW	261	5/16/2018 12:57	1526461038	0.8	28.06	0.28	0	0.9	2	0.14
698	D1	-1.3253	36.7537	99	1798.3	SW	261	5/16/2018 12:57	1526461042	0.8	27.5	-0.56	0	1.3	4	-0.14
699	D1	-1.32592	36.74972	45	1806.6	SW	261	5/16/2018 12:57	1526461061	0.8	12.5	-15	0	8.3	19	-0.79
700	D1	-1.326	36.74923	36	1808.1	SW	261	5/16/2018 12:57	1526461067	0.8	10	-2.5	0	1.5	6	-0.42
701	D1	-1.32609	36.74866	55	1807.5	SW	261	5/16/2018 12:57	1526461072	0.8	15.28	5.28	0	-0.6	5	1.06
702	D1	-1.32617	36.7482	66	1807.2	SW	261	5/16/2018 12:57	1526461075	0.8	18.33	3.05	0	-0.3	3	1.02
703	D1	-1.32625	36.74768	72	1807.6	SW	260	5/16/2018 12:57	1526461078	0.8	20	1.67	-1	0.4	3	0.56
704	D1	-1.32638	36.74652	81	1808.4	SW	268	5/16/2018 12:58	1526461084	0.8	22.5	2.5	8	0.8	6	0.42
705	D1	-1.32635	36.74589	83	1808.9	NW	275	5/16/2018 12:58	1526461087	0.8	23.06	0.56	7	0.5	3	0.19
706	D1	-1.32625	36.74526	86	1810	NW	281	5/16/2018 12:58	1526461090	0.8	23.89	0.83	6	1.1	3	0.28
707	D1	-1.32565	36.74358	91	1811.8	NW	294	5/16/2018 12:58	1526461098	0.8	25.28	1.39	13	1.8	8	0.17
708	D1	-1.32546	36.74316	92	1811.8	NW	294	5/16/2018 12:58	1526461100	0.8	25.56	0.28	0	0	2	0.14
709	D1	-1.32527	36.74273	93	1811.8	NW	294	5/16/2018 12:58	1526461102	0.8	25.83	0.27	0	0	2	0.14
710	D1	-1.32339	36.73857	99	1809.2	NW	296	5/16/2018 12:58	1526461121	0.8	27.5	1.67	2	-2.6	19	0.09
711	D1	-1.32225	36.73694	100	1809.5	NW	313	5/16/2018 12:58	1526461129	0.8	27.78	0.28	17	0.3	8	0.04
712	D1	-1.32188	36.73659	101	1809.7	NW	317	5/16/2018 12:58	1526461131	0.8	28.06	0.28	4	0.2	2	0.14
713	D1	-1.3215	36.73626	100	1810.1	NW	319	5/16/2018 12:58	1526461133	0.8	27.78	-0.28	2	0.4	2	-0.14
714	D1	-1.32112	36.73594	100	1810.8	NW	319	5/16/2018 12:58	1526461135	0.8	27.78	0	0	0.7	2	0
715	D1	-1.32073	36.73562	100	1811.5	NW	319	5/16/2018 12:58	1526461137	0.8	27.78	0	0	0.7	2	0
716	D1	-1.32035	36.73529	100	1812.2	NW	319	5/16/2018 12:58	1526461139	0.8	27.78	0	0	0.7	2	0
717	D1	-1.31997	36.73497	100	1813	NW	319	5/16/2018 12:59	1526461141	0.8	27.78	0	0	0.8	2	0
718	D1	-1.31959	36.73465	100	1813.8	NW	319	5/16/2018 12:59	1526461143	0.8	27.78	0	0	0.8	2	0
719	D1	-1.3192	36.73432	100	1814.6	NW	319	5/16/2018 12:59	1526461145	0.8	27.78	0	0	0.8	2	0
720	D1	-1.31882	36.73399	100	1815.5	NW	319	5/16/2018 12:59	1526461147	0.8	27.78	0	0	0.9	2	0
721	D1	-1.31844	36.73367	102	1816.4	NW	319	5/16/2018 12:59	1526461149	0.8	28.33	0.55	0	0.9	2	0.27
722	D1	-1.31726	36.73265	105	1817.7	NW	319	5/16/2018 12:59	1526461155	0.8	29.17	0.84	0	1.3	6	0.14
723	D1	-1.31685	36.73231	107	1817.4	NW	320	5/16/2018 12:59	1526461157	0.8	29.72	0.55	1	-0.3	2	0.27
724	D1	-1.31642	36.73199	106	1816.9	NW	323	5/16/2018 12:59	1526461159	0.8	29.44	-0.28	3	-0.5	2	-0.14
725	D1	-1.31596	36.73171	107	1816.3	NW	329	5/16/2018 12:59	1526461161	0.8	29.72	0.28	6	-0.6	2	0.14
726	D1	-1.31548	36.73145	108	1816	NW	334	5/16/2018 12:59	1526461163	0.9	30	0.28	5	-0.3	2	0.14
727	D1	-1.3112	36.7296	77	1819.8	NW	317	5/16/2018 12:59	1526461182	0.8	21.39	-8.61	-17	3.8	19	-0.45
728	D1	-1.31086	36.72925	64	1820.9	NW	313	5/16/2018 12:59	1526461185	0.8	17.78	-3.61	-4	1.1	3	-1.2
729	D1	-1.31064	36.72878	51	1821.2	NW	284	5/16/2018 12:59	1526461189	0.8	14.17	-3.61	-29	0.3	4	-0.9
730	D1	-1.31065	36.72852	53	1821	SW	263	5/16/2018 12:59	1526461191	0.8	14.72	0.55	-21	-0.2	2	0.28
731	D1	-1.31076	36.72824	58	1821.3	SW	245	5/16/2018 12:59	1526461193	0.8	16.11	1.39	-18	0.3	2	0.69
732	D1	-1.31103	36.72785	62	1823.4	SW	237	5/16/2018 12:59	1526461196	0.8	17.22	1.11	-8	2.1	3	0.37
733	D1	-1.31118	36.72742	61	1824.5	SW	261	5/16/2018 12:59	1526461199	0.8	16.94	-0.28	24	1.1	3	-0.09
734	D1	-1.3111	36.72697	62	1824.7	NW	292	5/16/2018 1:00	1526461202	0.9	17.22	0.28	31	0.2	3	0.09
735	D1	-1.3109	36.72672	64	1825	NW	310	5/16/2018 1:00	1526461204	0.8	17.78	0.56	18	0.3	2	0.28
736	D1	-1.31068	36.7265	61	1824.9	NW	316	5/16/2018 1:00	1526461206	0.8	16.94	-0.84	6	-0.1	2	-0.42
737	D1	-1.31038	36.7261	44	1825.3	NW	288	5/16/2018 1:00	1526461210	0.8	12.22	-4.72	-28	0.4	4	-1.18
738	D1	-1.31036	36.72584	3	1828.3	SW	263	5/16/2018 1:00	1526461217	0.8	0.83	-11.39	-25	3	7	-1.63
739	D1	-1.31055	36.72524	4	1833.1	SW	247	5/16/2018 1:01	1526461319	0.8	1.11	0.28	-16	4.8	102	0
740	D1	-1.31125	36.72429	5	1834.7	SW	231	5/16/2018 1:04	1526461469	0.8	1.39	0.28	-16	1.6	150	0
741	D1	-1.31715	36.71972	6	1842.7	SE	99	5/16/2018 1:10	1526461800	0.9	1.67	0.28	-132	8	331	0
742	D1	-1.31721	36.71986	5	1840.9	SE	149	5/16/2018 1:10	1526461811	0.9	1.39	-0.28	50	-1.8	11	-0.03
743	D1	-1.31742	36.71985	2	1835.2	NE	4	5/16/2018 1:14	1526462078	0.9	0.56	-0.83	-145	-5.7	267	0
744	D1	-1.31742	36.71985	2	1835.2	SE	178	5/16/2018 1:14	1526462089	0.9	0.56	0	174	0	11	0
745	D1	-1.31744	36.71985	2	1835.6	SW	267	5/16/2018 1:15	1526462158	0.9	0.56	0	89	0.4	69	0
746	D1	-1.31744	36.71985	2	1835.9	SE	102	5/16/2018 1:16	1526462165	0.9	0.56	0	-165	0.3	7	0
747	D1	-1.31744	36.71985	0	1835.8	SE	111	5/16/2018 1:26	1526462795	0.9	0	-0.56	9	-0.1	630	0
748	D1	-1.31744	36.71985	0	1835.8	SE	111	5/16/2018 1:36	1526463397	0.9	0	0	0	0	602	0
749	D1	-1.31744	36.71985	0	1835.8	SE	111	5/16/2018 1:46	1526463998	0.9	0	0	0	0	601	0
750	D1	-1.31744	36.71985	0	1835.8	SE	111	5/16/2018 1:56	1526464599	0.9	0	0	0	0	601	0
751	D1	-1.31744	36.71985	0	1835.8	SE	111	5/16/2018 2:06	1526465200	0.9	0	0	0	0	601	0

752	D1	-1.31745	36.71989	0	1836.4	SE	111	5/16/2018 2:16	1526465802	0.9	0	0	0	0.6	602	0
753	D1	-1.31745	36.71989	0	1837.9	SE	111	5/16/2018 2:26	1526466403	0.8	0	0	0	1.5	601	0
754	D1	-1.31745	36.71989	0	1837.9	SE	111	5/16/2018 2:36	1526467004	0.8	0	0	0	0	601	0
755	D1	-1.31745	36.71989	0	1837.9	SE	111	5/16/2018 2:46	1526467605	0.8	0	0	0	0	601	0
756	D1	-1.31745	36.71989	0	1837.9	SE	111	5/16/2018 2:56	1526468207	0.8	0	0	0	0	602	0
757	D1	-1.31745	36.71989	0	1837.9	SE	111	5/16/2018 3:06	1526468808	0.8	0	0	0	0	601	0
758	D1	-1.31745	36.71989	0	1837.9	SE	111	5/16/2018 3:16	1526469409	0.8	0	0	0	0	601	0
759	D1	-1.31745	36.71989	0	1837.9	SE	111	5/16/2018 3:26	1526470010	0.8	0	0	0	0	601	0
760	D1	-1.31744	36.71988	2	1837.5	NW	292	5/16/2018 3:33	1526470385	0.8	0.56	0.56	181	-0.4	375	0
761	D1	-1.31743	36.71987	4	1837.7	NW	344	5/16/2018 3:33	1526470388	0.8	1.11	0.55	52	0.2	3	0.18
762	D1	-1.31741	36.71987	4	1837.8	NE	2	5/16/2018 3:33	1526470390	0.8	1.11	0	-342	0.1	2	0
763	D1	-1.31733	36.71986	2	1837.6	NW	348	5/16/2018 3:33	1526470414	0.8	0.56	-0.55	346	-0.2	24	-0.02
764	D1	-1.31722	36.7198	5	1836.6	NW	294	5/16/2018 3:33	1526470428	0.8	1.39	0.83	-54	-1	14	0.06
765	D1	-1.3172	36.71977	6	1836.9	NW	292	5/16/2018 3:33	1526470430	0.9	1.67	0.28	-2	0.3	2	0.14
766	D1	-1.31712	36.7193	3	1841.3	SW	245	5/16/2018 3:34	1526470463	0.8	0.83	-0.84	-47	4.4	33	-0.03
767	D1	-1.31717	36.71926	5	1840.5	SW	197	5/16/2018 3:34	1526470470	0.8	1.39	0.56	-48	-0.8	7	0.08
768	D1	-1.31741	36.71905	7	1838	NW	273	5/16/2018 3:34	1526470494	0.8	1.94	0.55	76	-2.5	24	0.02
769	D1	-1.3174	36.71895	12	1838.4	NW	278	5/16/2018 3:34	1526470497	0.8	3.33	1.39	5	0.4	3	0.46
770	D1	-1.31741	36.71876	13	1836.5	SW	208	5/16/2018 3:35	1526470516	0.8	3.61	0.28	-70	-1.9	19	0.01
771	D1	-1.31772	36.71869	32	1837.9	SW	189	5/16/2018 3:35	1526470521	0.8	8.89	5.28	-19	1.4	5	1.06
772	D1	-1.3182	36.71859	41	1841	SW	191	5/16/2018 3:35	1526470526	0.8	11.39	2.5	2	3.1	5	0.5
773	D1	-1.31877	36.71848	47	1843.3	SW	190	5/16/2018 3:35	1526470531	0.8	13.06	1.67	-1	2.3	5	0.33
774	D1	-1.31928	36.7184	52	1844.5	SW	189	5/16/2018 3:35	1526470535	0.8	14.44	1.38	-1	1.2	4	0.35
775	D1	-1.31982	36.71832	54	1845.6	SW	189	5/16/2018 3:35	1526470539	0.8	15	0.56	0	1.1	4	0.14
776	D1	-1.32188	36.718	54	1848.1	SW	190	5/16/2018 3:35	1526470554	0.8	15	0	1	2.5	15	0
777	D1	-1.32242	36.71792	55	1848.1	SW	188	5/16/2018 3:35	1526470558	0.8	15.28	0.28	-2	0	4	0.07
778	D1	-1.32297	36.71784	55	1848	SW	189	5/16/2018 3:36	1526470562	0.9	15.28	0	1	-0.1	4	0
779	D1	-1.32351	36.71776	54	1848.5	SW	189	5/16/2018 3:36	1526470566	0.8	15	-0.28	0	0.5	4	-0.07
780	D1	-1.32404	36.71768	54	1849.8	SW	189	5/16/2018 3:36	1526470570	0.8	15	0	0	1.3	4	0
781	D1	-1.32458	36.7176	54	1850.9	SW	188	5/16/2018 3:36	1526470574	0.8	15	0	-1	1.1	4	0
782	D1	-1.3251	36.71752	51	1851	SW	188	5/16/2018 3:36	1526470578	0.8	14.17	-0.83	0	0.1	4	-0.21
783	D1	-1.3256	36.71744	53	1850.8	SW	188	5/16/2018 3:36	1526470582	0.8	14.72	0.55	0	-0.2	4	0.14
784	D1	-1.32615	36.71736	57	1850.7	SW	189	5/16/2018 3:36	1526470586	0.8	15.83	1.11	1	-0.1	4	0.28
785	D1	-1.32672	36.71727	56	1850.3	SW	188	5/16/2018 3:36	1526470590	0.8	15.56	-0.27	-1	-0.4	4	-0.07
786	D1	-1.32727	36.71718	56	1849.7	SW	189	5/16/2018 3:36	1526470594	0.8	15.56	0	1	-0.6	4	0
787	D1	-1.3278	36.7171	53	1849.1	SW	189	5/16/2018 3:36	1526470598	0.8	14.72	-0.84	0	-0.6	4	-0.21
788	D1	-1.32823	36.71703	39	1849.6	SW	189	5/16/2018 3:36	1526470602	0.8	10.83	-3.89	0	0.5	4	-0.97
789	D1	-1.32964	36.71681	56	1849.6	SW	189	5/16/2018 3:36	1526470615	0.8	15.56	4.73	0	0	13	0.36
790	D1	-1.33023	36.71671	62	1851.6	SW	189	5/16/2018 3:36	1526470619	0.8	17.22	1.66	0	2	4	0.42
791	D1	-1.33072	36.71662	66	1852.3	SW	189	5/16/2018 3:37	1526470622	0.8	18.33	1.11	0	0.7	3	0.37
792	D1	-1.33124	36.71654	69	1852.4	SW	189	5/16/2018 3:37	1526470625	0.8	19.17	0.84	0	0.1	3	0.28
793	D1	-1.33176	36.71647	69	1852	SW	189	5/16/2018 3:37	1526470628	0.8	19.17	0	0	-0.4	3	0
794	D1	-1.33227	36.71639	68	1851.9	SW	189	5/16/2018 3:37	1526470631	0.8	18.89	-0.28	0	-0.1	3	-0.09
795	D1	-1.33273	36.71632	60	1851.8	SW	189	5/16/2018 3:37	1526470634	0.9	16.67	-2.22	0	-0.1	3	-0.74
796	D1	-1.33326	36.71628	31	1852	SW	186	5/16/2018 3:37	1526470640	0.8	8.61	-8.06	-3	0.2	6	-1.34
797	D1	-1.33382	36.71616	41	1855.3	SW	189	5/16/2018 3:37	1526470647	0.8	11.39	2.78	3	3.3	7	0.4
798	D1	-1.33428	36.71609	50	1857.5	SW	189	5/16/2018 3:37	1526470651	0.8	13.89	2.5	0	2.2	4	0.63
799	D1	-1.33483	36.716	57	1859.5	SW	189	5/16/2018 3:37	1526470655	0.9	15.83	1.94	0	2	4	0.49
800	D1	-1.33528	36.71593	63	1859.4	SW	188	5/16/2018 3:37	1526470658	0.8	17.5	1.67	-1	-0.1	3	0.56
801	D1	-1.33577	36.71586	66	1859.1	SW	189	5/16/2018 3:37	1526470661	0.9	18.33	0.83	1	-0.3	3	0.28
802	D1	-1.33798	36.71555	58	1858.9	SW	188	5/16/2018 3:37	1526470675	0.8	16.11	-2.22	-1	-0.2	14	-0.16
803	D1	-1.33855	36.71546	56	1860.2	SW	190	5/16/2018 3:37	1526470679	0.8	15.56	-0.55	2	1.3	4	-0.14
804	D1	-1.339	36.71524	51	1860.5	SW	216	5/16/2018 3:38	1526470683	0.8	14.17	-1.39	26	0.3	4	-0.35
805	D1	-1.33939	36.71488	56	1861.8	SW	222	5/16/2018 3:38	1526470687	0.8	15.56	1.39	6	1.3	4	0.35
806	D1	-1.33974	36.7146	60	1862	SW	218	5/16/2018 3:38	1526470690	0.8	16.67	1.11	-4	0.2	3	0.37
807	D1	-1.34076	36.7141	56	1859.8	SW	190	5/16/2018 3:38	1526470698	0.8	15.56	-1.11	-28	-2.2	8	-0.14
808	D1	-1.34129	36.71409	50	1858.5	SE	175	5/16/2018 3:38	1526470702	0.8	13.89	-1.67	-15	-1.3	4	-0.42
809	D1	-1.34152	36.71415	47	1858	SE	164	5/16/2018 3:38	1526470704	0.9	13.06	-0.83	-11	-0.5	2	-0.42
810	D1	-1.34178	36.71426	34	1855.7	SE	160	5/16/2018 3:38	1526470707	0.8	9.44	-3.62	-4	-2.3	3	-1.21
811	D1	-1.34225	36.71447	37	1853.6	SE	158	5/16/2018 3:38	1526470715	0.8	10.28	0.84	-2	-2.1	8	0.11
812	D1	-1.34368	36.71473	19	1853.6	SW	189	5/16/2018 3:38	1526470734	0.9	5.28	-5	31	0	19	-0.26
813	D1	-1.3442	36.71465	42	1854	SW	188	5/16/2018 3:39	1526470741	0.9	11.67	6.39	-1	0.4	7	0.91
814	D1	-1.34467	36.71458	49	1854.7	SW	188	5/16/2018 3:39	1526470745	0.8	13.61	1.94	0	0.7	4	0.49
815	D1	-1.3452	36.7145	55	1855.7	SW	189	5/16/2018 3:39	1526470749	0.9	15.28	1.67	1	1	4	0.42
816	D1	-1.34578	36.71442	60	1855.2	SW	188	5/16/2018 3:39	1526470753	0.9	16.67	1.39	-1	-0.5	4	0.35
817	D1	-1.34625	36.71435	62	1855.1	SW	188	5/16/2018 3:39	1526470756	0.9	17.22	0.55	0	-0.1	3	0.18
818	D1	-1.34673	36.71428	66	1854.8	SW	188	5/16/2018 3:39	1526470759	0.9	18.33	1.11	0	-0.3	3	0.37
819	D1	-1.34723	36.7142	70	1854.6	SW	189	5/16/2018 3:39	1526470762	0.9	19.44	1.11	1	-0.2	3	0.37
820	D1	-1.34777	36.71412	72	1854.6	SW	188	5/16/2018 3:39	1526470765	0.8	20	0.56	-1	0	3	0.19
821	D1	-1.34831	36.71403	71	1855.6	SW	188	5/16/2018 3:39	1526470768	0.9	19.72	-0.28	0	1	3	-0.09
822	D1	-1.34883	36.71396	69	1857.3	SW	188	5/16/2018 3:39	1526470771	1	19.17	-0.55	0	1.7	3	-0.18
823	D1	-1.34936	36.71389	71	1858.1	SW	188	5/16/2018 3:39	1526470774	0.9	19.72	0.55	0	0.8	3	0.18
824	D1	-1.3499	36.71381	73	1859.2	SW	188	5/16/2018 3:39	1526470777	0.8	20.28	0.56	0	1.1	3	0.19
825	D1	-1.35045	36.71372	74	1859.4	SW	188	5/16/2018 3:39	1526470780	0.9	20.56	0.28	0	0.2	3	0.09
826	D1	-1.35283	36.71336	60	1857.6	SW	188	5/16/2018 3:39	1526470794	0.9	16.67	-3.89	0	-1.8	14	-0.28
827	D1	-1.35331	36.71327	25	1859.1	SW	191	5/16/2018 3:39	1526470799	0.9	6.94	-9.73	3	1.5	5	-1.95
828	D1	-1.3538	36.71319	33	1860.1	SW	189	5/16/2018 3:40	1526470807	0.9	9.17	2.23	-2	1	8	0.28
829	D1	-1.35414	36.7133	22	1859.1	SE	118	5/16/2018 3:40	1526470813	0.9	6.11	-3.06	-71	-1	6	-0.51
830	D1	-1.35416	36.71343	18	1858.3	SE	96	5/16/2018 3:40	1526470816	0.9	5	-1.11	-22	-0.8	3	-0.37
831	D1	-1.35419	36.71396	43	1859.1	SE	96	5/16/2018 3:40	1526470822	0.9	11.94	6.94	0	0.8	6	1.16
832	D1	-1.35424	36.71446	50	1860.2	SE	96	5/16/2018 3:40	1526470826	0.9	13.89	1.95	0	1.1	4	0.49
833	D1	-1.3543	36.71499	55	1858.8	SE	97	5/16/2018 3:40	1526470830	0.9	15.28	1.39	1	-1.4	4	0.35
834	D1	-1.35437	36.71558	59	1854.6	SE	97	5/16/2018 3:40	1526470834	0.9	16.39	1.11	0	-4.2	4	0.28
835	D1	-1.35442	36.71604	62	1852.2	SE	96	5/16/2018 3:40	1526470837	0.9	17.22	0.83	-1	-2.4	3	0.28

836	D1	-1.35447	36.7165	62	1850.4	SE	97	5/16/2018 3:40	1526470840	0.9	17.22	0	1	-1.8	3	0
837	D1	-1.35467	36.71833	35	1845.7	SE	96	5/16/2018 3:40	1526470855	0.9	9.72	-7.5	-1	-4.7	15	-0.5
838	D1	-1.35473	36.7188	40	1846.4	SE	97	5/16/2018 3:41	1526470860	0.9	11.11	1.39	1	0.7	5	0.28
839	D1	-1.35479	36.71936	48	1847.1	SE	96	5/16/2018 3:41	1526470865	0.9	13.33	2.22	-1	0.7	5	0.44
840	D1	-1.35485	36.71985	48	1847	SE	96	5/16/2018 3:41	1526470869	0.9	13.33	0	0	-0.1	4	0
841	D1	-1.3549	36.72036	51	1846	SE	96	5/16/2018 3:41	1526470873	0.9	14.17	0.84	0	-1	4	0.21
842	D1	-1.35496	36.72087	51	1844.9	SE	97	5/16/2018 3:41	1526470877	0.9	14.17	0	1	-1.1	4	0
843	D1	-1.35501	36.72138	50	1844.5	SE	96	5/16/2018 3:41	1526470881	0.9	13.89	-0.28	-1	-0.4	4	-0.07
844	D1	-1.35505	36.7219	50	1844.4	SE	94	5/16/2018 3:41	1526470885	0.9	13.89	0	-2	-0.1	4	0
845	D1	-1.35511	36.7224	51	1844.7	SE	96	5/16/2018 3:41	1526470889	0.9	14.17	0.28	2	0.3	4	0.07
846	D1	-1.35517	36.7229	50	1843.5	SE	96	5/16/2018 3:41	1526470893	0.9	13.89	-0.28	0	-1.2	4	-0.07
847	D1	-1.35523	36.72348	49	1842.7	SE	96	5/16/2018 3:41	1526470898	0.9	13.61	-0.28	0	-0.8	5	-0.06
848	D1	-1.35529	36.72399	53	1843.1	SE	97	5/16/2018 3:41	1526470902	0.9	14.72	1.11	1	0.4	4	0.28
849	D1	-1.35581	36.72572	52	1840.1	SE	119	5/16/2018 3:41	1526470916	0.9	14.44	-0.28	22	-3	14	-0.02
850	D1	-1.35597	36.72616	44	1839.8	SE	96	5/16/2018 3:42	1526470920	0.9	12.22	-2.22	-23	-0.3	4	-0.56
851	D1	-1.35593	36.72638	27	1837.9	NE	63	5/16/2018 3:42	1526470923	0.9	7.5	-4.72	-33	-1.9	3	-1.57
852	D1	-1.35517	36.72712	3	1839.2	NW	358	5/16/2018 3:43	1526470983	0.9	0.83	-6.67	295	1.3	60	-0.11
853	D1	-1.35515	36.72712	4	1839.3	NE	5	5/16/2018 3:43	1526470986	0.9	1.11	0.28	-353	0.1	3	0.09
854	D1	-1.3551	36.72718	3	1835.3	SW	226	5/16/2018 3:43	1526470997	0.9	0.83	-0.28	221	-4	11	-0.03
855	D1	-1.35512	36.72712	0	1829.2	SW	253	5/16/2018 3:46	1526471213	0.9	0	-0.83	27	-6.1	216	0
856	D1	-1.35512	36.72712	0	1829.2	SW	253	5/16/2018 3:56	1526471814	0.9	0	0	0	0	601	0
857	D1	-1.35512	36.72712	0	1829.2	SW	253	5/16/2018 4:06	1526472415	0.9	0	0	0	0	601	0
858	D1	-1.35512	36.72712	0	1829.2	SW	253	5/16/2018 4:16	1526473017	1	0	0	0	0	602	0
859	D1	-1.35512	36.72712	0	1829.2	SW	253	5/16/2018 4:26	1526473618	1	0	0	0	0	601	0
860	D1	-1.35512	36.72712	0	1829.2	SW	253	5/16/2018 4:36	1526474219	0.9	0	0	0	0	601	0
861	D1	-1.35512	36.72712	0	1829.2	SW	253	5/16/2018 4:47	1526474820	0.9	0	0	0	0	601	0
862	D1	-1.35512	36.72713	0	1835.2	SW	253	5/16/2018 4:57	1526475422	0.8	0	0	0	6	602	0
863	D1	-1.35512	36.72711	0	1835.2	SW	253	5/16/2018 5:07	1526476023	0.7	0	0	0	0	601	0
864	D1	-1.35512	36.72711	0	1835.2	SW	253	5/16/2018 5:17	1526476624	0.7	0	0	0	0	601	0
865	D1	-1.35512	36.72711	0	1835.2	SW	253	5/16/2018 5:27	1526477225	0.8	0	0	0	0	601	0
866	D1	-1.35512	36.72711	0	1835.2	SW	253	5/16/2018 5:37	1526477827	0.8	0	0	0	0	602	0
867	D1	-1.35512	36.72711	0	1835.2	SW	253	5/16/2018 5:47	1526478428	0.9	0	0	0	0	601	0
868	D1	-1.35512	36.72711	0	1835.2	SW	253	5/16/2018 5:57	1526479029	0.8	0	0	0	0	601	0
869	D1	-1.35512	36.72711	0	1835.2	SW	253	5/16/2018 6:07	1526479630	0.8	0	0	0	0	601	0
870	D1	-1.35514	36.72709	4	1836.2	NW	278	5/16/2018 6:14	1526480085	0.8	1.11	1.11	25	1	455	0
871	D1	-1.35515	36.72665	4	1837.4	SW	262	5/16/2018 6:15	1526480109	0.8	1.11	0	-16	1.2	24	0
872	D1	-1.3552	36.72653	9	1838.9	SW	216	5/16/2018 6:15	1526480115	0.8	2.5	1.39	-46	1.5	6	0.23
873	D1	-1.35559	36.72643	18	1837.3	SW	191	5/16/2018 6:15	1526480124	0.8	5	2.5	-25	-1.6	9	0.28
874	D1	-1.35587	36.72641	10	1834.6	SE	166	5/16/2018 6:15	1526480132	0.8	2.78	-2.22	-25	-2.7	8	-0.28
875	D1	-1.35587	36.72661	21	1834.4	NE	67	5/16/2018 6:15	1526480138	0.8	5.83	3.05	-99	-0.2	6	0.51
876	D1	-1.35569	36.72709	33	1837.7	NE	75	5/16/2018 6:15	1526480145	0.8	9.17	3.34	8	3.3	7	0.48
877	D1	-1.35567	36.72757	39	1836.4	SE	94	5/16/2018 6:15	1526480150	0.8	10.83	1.66	19	-1.3	5	0.33
878	D1	-1.35572	36.7281	42	1834.6	SE	95	5/16/2018 6:15	1526480155	0.8	11.67	0.84	1	-1.8	5	0.17
879	D1	-1.35577	36.72865	46	1832.7	SE	95	5/16/2018 6:16	1526480160	0.8	12.78	1.11	0	-1.9	5	0.22
880	D1	-1.35591	36.7304	54	1833.3	NE	86	5/16/2018 6:16	1526480174	0.8	15	2.22	-9	0.6	14	0.16
881	D1	-1.35586	36.73094	54	1832.9	NE	84	5/16/2018 6:16	1526480178	0.8	15	0	-2	-0.4	4	0
882	D1	-1.3558	36.73146	51	1833.2	NE	83	5/16/2018 6:16	1526480182	0.8	14.17	-0.83	-1	0.3	4	-0.21
883	D1	-1.35575	36.73195	48	1834	NE	84	5/16/2018 6:16	1526480186	0.8	13.33	-0.84	1	0.8	4	-0.21
884	D1	-1.3557	36.73241	47	1833.8	NE	83	5/16/2018 6:16	1526480190	0.8	13.06	-0.27	-1	-0.2	4	-0.07
885	D1	-1.35563	36.73296	43	1833.1	NE	82	5/16/2018 6:16	1526480195	0.8	11.94	-1.12	-1	-0.7	5	-0.22
886	D1	-1.35556	36.73347	40	1832	NE	82	5/16/2018 6:16	1526480200	0.8	11.11	-0.83	0	-1.1	5	-0.17
887	D1	-1.3555	36.73398	30	1831.1	NE	82	5/16/2018 6:16	1526480207	0.8	8.33	-2.78	0	-0.9	7	-0.4
888	D1	-1.35545	36.73446	22	1830.3	NE	80	5/16/2018 6:16	1526480215	0.8	6.11	-2.22	-2	-0.8	8	-0.28
889	D1	-1.3554	36.73491	25	1829.8	NE	83	5/16/2018 6:17	1526480222	0.8	6.94	0.83	3	-0.5	7	0.12
890	D1	-1.35522	36.73638	52	1824.3	NE	82	5/16/2018 6:17	1526480236	0.8	14.44	7.5	-1	-5.5	14	0.54
891	D1	-1.35517	36.7369	53	1824.2	NE	83	5/16/2018 6:17	1526480240	0.8	14.72	0.28	1	-0.1	4	0.07
892	D1	-1.3551	36.73745	56	1824.4	NE	83	5/16/2018 6:17	1526480244	0.8	15.56	0.84	0	0.2	4	0.21
893	D1	-1.35504	36.73802	59	1824.1	NE	83	5/16/2018 6:17	1526480248	0.8	16.39	0.83	0	-0.3	4	0.21
894	D1	-1.35497	36.73863	62	1824.1	NE	82	5/16/2018 6:17	1526480252	0.8	17.22	0.83	-1	0	4	0.21
895	D1	-1.3549	36.7391	64	1823.9	NE	82	5/16/2018 6:17	1526480255	0.8	17.78	0.56	0	-0.2	3	0.19
896	D1	-1.35484	36.73959	65	1823.6	NE	82	5/16/2018 6:17	1526480258	0.8	18.06	0.28	0	-0.3	3	0.09
897	D1	-1.35478	36.74007	66	1823.3	NE	82	5/16/2018 6:17	1526480261	0.8	18.33	0.27	0	-0.3	3	0.09
898	D1	-1.35471	36.74056	65	1823.3	NE	82	5/16/2018 6:17	1526480264	0.8	18.06	-0.27	0	0	3	-0.09
899	D1	-1.35459	36.7416	56	1823.9	NE	81	5/16/2018 6:17	1526480271	0.8	15.56	-2.5	-1	0.6	7	-0.36
900	D1	-1.35452	36.74205	28	1823.6	NE	82	5/16/2018 6:17	1526480276	0.8	7.78	-7.78	1	-0.3	5	-1.56
901	D1	-1.3544	36.74311	21	1821.5	NE	79	5/16/2018 6:18	1526480294	0.8	5.83	-1.95	-3	-2.1	18	-0.11
902	D1	-1.35433	36.74361	37	1821.7	NE	83	5/16/2018 6:18	1526480300	0.8	10.28	4.45	4	0.2	6	0.74
903	D1	-1.35428	36.74414	35	1819.3	NE	84	5/16/2018 6:18	1526480309	0.8	9.72	-0.56	1	-2.4	9	-0.06
904	D1	-1.35422	36.74462	52	1818.1	NE	81	5/16/2018 6:18	1526480313	0.8	14.44	4.72	-3	-1.2	4	1.18
905	D1	-1.35414	36.74519	58	1817.5	NE	82	5/16/2018 6:18	1526480317	0.8	16.11	1.67	1	-0.6	4	0.42
906	D1	-1.35407	36.74577	56	1816.9	NE	83	5/16/2018 6:18	1526480321	0.8	15.56	-0.55	1	-0.6	4	-0.14
907	D1	-1.35438	36.74668	25	1813.1	SW	194	5/16/2018 6:19	1526480372	0.8	6.94	-8.62	111	-3.8	51	-0.17
908	D1	-1.35486	36.74657	16	1812.4	SW	187	5/16/2018 6:19	1526480383	0.8	4.44	-2.5	-7	-0.7	11	-0.23
909	D1	-1.35533	36.74654	39	1812.9	S	180	5/16/2018 6:19	1526480389	0.8	10.83	6.39	-7	0.5	6	1.07
910	D1	-1.3559	36.74661	48	1813.1	SE	173	5/16/2018 6:19	1526480394	0.8	13.33	2.5	-7	0.2	5	0.5
911	D1	-1.3564	36.74667	49	1812.9	SE	173	5/16/2018 6:19	1526480398	0.8	13.61	0.28	0	-0.2	4	0.07
912	D1	-1.35688	36.74674	46	1812.7	SE	173	5/16/2018 6:20	1526480402	0.8	12.78	-0.83	0	-0.2	4	-0.21
913	D1	-1.35844	36.74691	46	1811.3	SE	174	5/16/2018 6:20	1526480416	0.8	12.78	0	1	-1.4	14	0
914	D1	-1.3589	36.74697	46	1810.8	SE	173	5/16/2018 6:20	1526480420	0.8	12.78	0	-1	-0.5	4	0
915	D1	-1.35937	36.74703	47	1810.6	SE	173	5/16/2018 6:20	1526480424	0.8	13.06	0.28	0	-0.2	4	0.07
916	D1	-1.35984	36.74708	47	1810.2	SE	172	5/16/2018 6:20	1526480428	0.8	13.06	0	-1	-0.4	4	0
917	D1	-1.3603	36.74714	47	1809.9	SE	173	5/16/2018 6:20	1526480432	0.8	13.06	0	1	-0.3	4	0
918	D1	-1.36077	36.74719	46	1809.4	SE	174	5/16/2018 6:20	1526480436	0.8	12.78	-0.28	1	-0.5	4	-0.07
919	D1	-1.36126	36.74725	51	1809.2	SE	173	5/16/2018 6:20	1526480440	0.8	14.17	1.39	-1	-0.2	4	0.35

920	D1	-1.36179	36.74731	54	1809.2	SE	173	5/16/2018 6:20	1526480444	0.8	15	0.83	0	0	4	0.21
921	D1	-1.36232	36.74737	51	1809	SE	174	5/16/2018 6:20	1526480448	0.8	14.17	-0.83	1	-0.2	4	-0.21
922	D1	-1.36286	36.74744	40	1807.8	SE	171	5/16/2018 6:20	1526480453	0.8	11.11	-3.06	-3	-1.2	5	-0.61
923	D1	-1.36381	36.74999	18	1804.8	NE	87	5/16/2018 6:21	1526480497	0.8	5	-6.11	-84	-3	44	-0.14
924	D1	-1.3637	36.75091	41	1801.7	NE	85	5/16/2018 6:21	1526480510	0.8	11.39	6.39	-2	-3.1	13	0.49
925	D1	-1.36364	36.75153	17	1800.8	NE	86	5/16/2018 6:21	1526480517	0.8	4.72	-6.67	1	-0.9	7	-0.95
926	D1	-1.36341	36.75332	41	1801.6	NE	83	5/16/2018 6:22	1526480534	0.8	11.39	6.67	-3	0.8	17	0.39
927	D1	-1.36334	36.7539	38	1801.8	NE	82	5/16/2018 6:22	1526480543	0.8	10.56	-0.83	-1	0.2	9	-0.09
928	D1	-1.36327	36.7544	55	1801.9	NE	82	5/16/2018 6:22	1526480547	0.8	15.28	4.72	0	0.1	4	1.18
929	D1	-1.36321	36.75485	60	1802	NE	82	5/16/2018 6:22	1526480550	0.8	16.67	1.39	0	0.1	3	0.46
930	D1	-1.36314	36.75538	31	1801.1	NE	83	5/16/2018 6:22	1526480555	0.8	8.61	-8.06	1	-0.9	5	-1.61
931	D1	-1.36319	36.75579	26	1800.3	SE	136	5/16/2018 6:22	1526480565	0.8	7.22	-1.39	53	-0.8	10	-0.14
932	D1	-1.36332	36.75584	29	1800.7	SE	164	5/16/2018 6:22	1526480567	0.8	8.06	0.84	28	0.4	2	0.42
933	D1	-1.36386	36.7559	36	1802.2	SE	175	5/16/2018 6:22	1526480573	0.8	10	1.94	11	1.5	6	0.32
934	D1	-1.3647	36.75595	19	1796.6	SE	173	5/16/2018 6:23	1526480594	0.8	5.28	-4.72	-2	-5.6	21	-0.22
935	D1	-1.36522	36.75601	32	1800.8	SE	176	5/16/2018 6:23	1526480601	0.8	8.89	3.61	3	4.2	7	0.52
936	D1	-1.36574	36.75608	43	1799	SE	175	5/16/2018 6:23	1526480606	0.8	11.94	3.05	-1	-1.8	5	0.61
937	D1	-1.36622	36.75612	45	1796.1	SE	174	5/16/2018 6:23	1526480610	0.8	12.5	0.56	-1	-2.9	4	0.14
938	D1	-1.36675	36.7562	40	1791.9	SE	170	5/16/2018 6:23	1526480617	0.8	11.11	-1.39	-4	-4.2	7	-0.2
939	D1	-1.36725	36.75627	31	1790.8	SE	174	5/16/2018 6:23	1526480622	0.8	8.61	-2.5	4	-1.1	5	-0.5
940	D1	-1.36775	36.75633	32	1789	SE	174	5/16/2018 6:23	1526480630	0.8	8.89	0.28	0	-1.8	8	0.04
941	D1	-1.36823	36.75639	22	1787.8	SE	172	5/16/2018 6:24	1526480640	0.8	6.11	-2.78	-2	-1.2	10	-0.28
942	D1	-1.3696	36.75652	35	1789.4	SE	177	5/16/2018 6:24	1526480655	0.8	9.72	3.61	5	1.6	15	0.24
943	D1	-1.37014	36.75658	35	1789.1	SE	172	5/16/2018 6:24	1526480664	0.8	9.72	0	-5	-0.3	9	0
944	D1	-1.37059	36.75664	47	1790.8	SE	173	5/16/2018 6:24	1526480668	0.8	13.06	3.34	1	1.7	4	0.84
945	D1	-1.37111	36.75671	30	1790.4	SE	171	5/16/2018 6:24	1526480673	0.8	8.33	-4.73	-2	-0.4	5	-0.95
946	D1	-1.37222	36.75682	41	1790	SE	173	5/16/2018 6:24	1526480686	0.8	11.39	3.06	2	-0.4	13	0.24
947	D1	-1.37275	36.75689	31	1790.7	SE	174	5/16/2018 6:24	1526480694	0.8	8.61	-2.78	1	0.7	8	-0.35
948	D1	-1.37325	36.75696	29	1790.4	SE	171	5/16/2018 6:25	1526480700	0.8	8.06	-0.55	-3	-0.3	6	-0.09
949	D1	-1.3733	36.75772	24	1789.2	NE	84	5/16/2018 6:25	1526480715	0.8	6.67	-1.39	-87	-1.2	15	-0.09
950	D1	-1.37324	36.75822	24	1782.1	NE	84	5/16/2018 6:25	1526480723	0.8	6.67	0	0	-7.1	8	0
951	D1	-1.37318	36.7587	38	1781.8	NE	83	5/16/2018 6:25	1526480729	0.8	10.56	3.89	-1	-0.3	6	0.65
952	D1	-1.37312	36.75919	23	1779.8	NE	83	5/16/2018 6:25	1526480736	0.8	6.39	-4.17	0	-2	7	-0.6
953	D1	-1.37208	36.76795	6	1764.2	NE	84	5/16/2018 6:29	1526480956	0.8	1.67	-4.72	1	-15.6	220	-0.02
954	D1	-1.37211	36.76852	26	1768.1	SE	137	5/16/2018 6:34	1526481286	0.8	7.22	5.55	53	3.9	330	0.02
955	D1	-1.37286	36.76895	7	1769	SE	156	5/16/2018 6:37	1526481424	0.8	1.94	-5.28	19	0.9	138	-0.04
956	D1	-1.37322	36.7691	10	1768.4	SE	158	5/16/2018 6:37	1526481438	0.8	2.78	0.84	2	-0.6	14	0.06
957	D1	-1.37381	36.76933	12	1769	SE	163	5/16/2018 6:38	1526481481	0.9	3.33	0.55	5	0.6	43	0.01
958	D1	-1.37435	36.76949	22	1770.1	SE	166	5/16/2018 6:38	1526481496	0.8	6.11	2.78	3	1.1	15	0.19
959	D1	-1.37482	36.76959	26	1767.3	SE	170	5/16/2018 6:38	1526481504	0.8	7.22	1.11	4	-2.8	8	0.14
960	D1	-1.37533	36.76967	24	1763.7	SE	171	5/16/2018 6:38	1526481512	0.8	6.67	-0.55	1	-3.6	8	-0.07
961	D1	-1.37619	36.76978	15	1765.2	SE	172	5/16/2018 6:39	1526481556	0.8	4.17	-2.5	1	1.5	44	-0.06
962	D1	-1.37668	36.76984	16	1765.4	SE	172	5/16/2018 6:39	1526481567	0.8	4.44	0.27	0	0.2	11	0.02
963	D1	-1.37727	36.76994	12	1752.7	SE	171	5/16/2018 6:39	1526481598	0.8	3.33	-1.11	-1	-12.7	31	-0.04
964	D1	-1.37814	36.77005	22	1747.2	SE	172	5/16/2018 6:40	1526481617	0.8	6.11	2.78	1	-5.5	19	0.15
965	D1	-1.37869	36.77013	13	1742.4	SE	170	5/16/2018 6:40	1526481636	0.8	3.61	-2.5	-2	-4.8	19	-0.13
966	D1	-1.37942	36.77023	9	1744.9	SE	171	5/16/2018 6:41	1526481677	0.8	2.5	-1.11	1	2.5	41	-0.03
967	D1	-1.38132	36.77049	18	1722	SE	171	5/16/2018 6:42	1526481762	0.8	5	2.5	0	-22.9	85	0.03
968	D1	-1.38184	36.77057	7	1722.5	SE	173	5/16/2018 6:42	1526481779	0.8	1.94	-3.06	2	0.5	17	-0.18
969	D1	-1.38239	36.77065	8	1720.6	SE	173	5/16/2018 6:43	1526481797	0.8	2.22	0.28	0	-1.9	18	0.02
970	D1	-1.38299	36.77073	9	1724.8	SE	174	5/16/2018 6:46	1526482011	0.8	2.5	0.28	1	4.2	214	0
971	D1	-1.38309	36.77076	6	1724	SE	173	5/16/2018 6:47	1526482025	0.8	1.67	-0.83	-1	-0.8	14	-0.06
972	D1	-1.38334	36.77078	2	1725	SW	182	5/16/2018 6:47	1526482050	0.8	0.56	-1.11	9	1	25	-0.04
973	D1	-1.38407	36.77087	21	1724.1	SE	170	5/16/2018 6:48	1526482115	0.8	5.83	5.27	-12	-0.9	65	0.08
974	D1	-1.38456	36.77094	18	1724.2	SE	172	5/16/2018 6:48	1526482124	0.8	5	-0.83	2	0.1	9	-0.09
975	D1	-1.38561	36.77109	8	1727.2	SE	173	5/16/2018 6:49	1526482166	0.8	2.22	-2.78	1	3	42	-0.07
976	D1	-1.38674	36.77107	12	1715.2	SW	200	5/16/2018 6:50	1526482236	0.8	3.33	1.11	27	-12	70	0.02
977	D1	-1.38719	36.77078	12	1712.2	SW	220	5/16/2018 6:50	1526482252	0.8	3.33	0	20	-3	16	0
978	D1	-1.38767	36.77034	8	1709.7	SW	222	5/16/2018 6:52	1526482321	0.8	2.22	-1.11	2	-2.5	69	-0.02
979	D1	-1.38773	36.77028	9	1710.4	SW	229	5/16/2018 6:52	1526482325	0.8	2.5	0.28	7	0.7	4	0.07
980	D1	-1.38801	36.77002	9	1707.8	SW	222	5/16/2018 6:52	1526482341	0.8	2.5	0	-7	-2.6	16	0
981	D1	-1.38838	36.76965	9	1704.6	SW	222	5/16/2018 6:52	1526482358	0.8	2.5	0	0	-3.2	17	0
982	D1	-1.38885	36.76906	7	1700.7	SW	244	5/16/2018 6:53	1526482398	0.8	1.94	-0.56	22	-3.9	40	-0.01
983	D1	-1.38925	36.76819	12	1701.3	SW	243	5/16/2018 6:54	1526482458	0.8	3.33	1.39	-1	0.6	60	0.02
984	D1	-1.38964	36.76768	9	1698.2	SW	224	5/16/2018 6:55	1526482501	0.8	2.5	-0.83	-19	-3.1	43	-0.02
985	D1	-1.39021	36.76721	23	1709.4	SW	218	5/16/2018 6:55	1526482531	0.8	6.39	3.89	-6	11.2	30	0.13
986	D1	-1.39055	36.76703	10	1711.7	SE	171	5/16/2018 6:55	1526482540	0.8	2.78	-3.61	-47	2.3	9	-0.4
987	D1	-1.39062	36.76709	14	1711.7	SE	130	5/16/2018 6:55	1526482543	0.8	3.89	1.11	-41	0	3	0.37
988	D1	-1.39078	36.76761	23	1716.2	SE	101	5/16/2018 6:55	1526482557	0.8	6.39	2.5	-29	4.5	14	0.18
989	D1	-1.3908	36.76806	22	1716.4	SE	91	5/16/2018 6:56	1526482565	0.8	6.11	-0.28	-10	0.2	8	-0.03
990	D1	-1.39075	36.76876	14	1716.9	NE	84	5/16/2018 6:56	1526482579	0.8	3.89	-2.22	-7	0.5	14	-0.16
991	D1	-1.39071	36.76923	20	1718.6	NE	81	5/16/2018 6:56	1526482591	0.8	5.56	1.67	-3	1.7	12	0.14
992	D1	-1.3907	36.76933	19	1718.7	NE	84	5/16/2018 6:56	1526482593	0.8	5.28	-0.28	3	0.1	2	-0.14
993	D1	-1.39071	36.76984	16	1718.5	NE	86	5/16/2018 6:56	1526482606	0.8	4.44	-0.84	2	-0.2	13	-0.06
994	D1	-1.39075	36.77041	20	1717.4	SE	101	5/16/2018 6:57	1526482627	0.8	5.56	1.12	15	-1.1	21	0.05
995	D1	-1.39088	36.77133	39	1717.4	SE	96	5/16/2018 6:57	1526482641	0.8	10.83	5.27	-5	0	14	0.38
996	D1	-1.39093	36.77183	32	1716.2	SE	96	5/16/2018 6:57	1526482647	0.8	8.89	-1.94	0	-1.2	6	-0.32
997	D1	-1.39096	36.77232	32	1715.4	SE	94	5/16/2018 6:57	1526482653	0.8	8.89	0	-2	-0.8	6	0
998	D1	-1.391	36.7728	19	1714.4	SE	96	5/16/2018 6:57	1526482661	0.8	5.28	-3.61	2	-1	8	-0.45
999	D1	-1.39101	36.77343	11	1711.5	NE	88	5/16/2018 6:58	1526482686	0.8	3.06	-2.22	-8	-2.9	25	-0.09
1000	D1	-1.39105	36.77418	27	1712.5	SE	93	5/16/2018 6:58	1526482700	0.8	7.5	4.44	5	1	14	0.32
1001	D1	-1.39173	36.77643	0	1709.2	SE	109	5/16/2018 7:07	1526483238	0.8	0	-7.5	16	-3.3	538	-0.01

APPENDIX E: SAMPLE MAIN STUDY DATA (DRIVER BEHAVIOUR DATASET)

Table 0.12. Driver D1 of the Public Service Vehicle Category

	Lat	Lon	Speed (km/h)	Altitude	Direction (Angle Changes)	GPSTime	GPS Signal Strength	Speed (m/s)	Change in Speed (m/s)	Change in Direction	Change in Altitude	Change in Time (s)	Accl/Decl (m/s^2)	SSD Based on Initial Speed (m)	Actual Distance to Stop (m)
1	-1.27357	36.81017	10	1682.4	310	1526640606	0.9	2.78							
2	-1.27349	36.8101	6	1682.2	305	1526640611	0.8	1.67	-1.11	-5	-0.2	5	-0.22	8.10	13.9
3	-1.27345	36.81006	4	1681.1	305	1526640616	0.8	1.11	-0.56	0	-1.1	5	-0.11	4.58	8.35
4	-1.27342	36.81	6	1681.1	298	1526640626	0.9	1.67	0.56	-7	0	10	0.06	2.96	11.1
5	-1.27339	36.80993	6	1681.7	294	1526640631	0.8	1.67	0	-4	0.6	5	0	4.58	8.35
6	-1.27335	36.80984	7	1682.1	299	1526640636	0.9	1.94	0.27	5	0.4	5	0.05	4.58	8.35
7	-1.27313	36.80953	9	1683.5	310	1526640654	0.8	2.5	0.56	11	1.4	18	0.03	5.43	34.92
8	-1.27297	36.80935	8	1685.4	308	1526640668	0.8	2.22	-0.28	-2	1.9	14	-0.02	7.18	35
9	-1.27268	36.80899	6	1685	311	1526640710	0.8	1.67	-0.55	3	-0.4	42	-0.01	6.29	93.24
10	-1.27252	36.80874	8	1690.2	316	1526640722	0.8	2.22	0.55	5	5.2	12	0.05	4.58	20.04
11	-1.27228	36.80846	21	1689.8	317	1526640731	0.8	5.83	3.61	1	-0.4	9	0.4	6.29	19.98
12	-1.27175	36.80793	42	1687.7	319	1526640738	0.8	11.67	5.84	2	-2.1	7	0.83	19.65	40.81
13	-1.2714	36.80763	48	1686.8	319	1526640742	0.8	13.33	1.66	0	-0.9	4	0.42	49.42	46.68
14	-1.27098	36.80726	51	1685.8	316	1526640746	0.8	14.17	0.84	-3	-1	4	0.21	59.79	53.32
15	-1.2706	36.80692	49	1685.6	317	1526640750	0.8	13.61	-0.56	1	-0.2	4	-0.14	65.28	56.68
16	-1.27024	36.80662	45	1688.1	316	1526640754	0.9	12.5	-1.11	-1	2.5	4	-0.28	61.60	54.44
17	-1.26989	36.80631	50	1690.1	318	1526640758	0.8	13.89	1.39	2	2	4	0.35	54.50	50
18	-1.26463	36.80161	11	1717.8	352	1526640836	0.9	3.06	-10.83	34	27.7	78	-0.14	63.43	1083.42
19	-1.26408	36.80146	19	1711.6	329	1526640847	0.8	5.28	2.22	-23	-6.2	11	0.2	9.03	33.66
20	-1.2637	36.80117	20	1713.7	316	1526640864	0.8	5.56	0.28	-13	2.1	17	0.02	17.35	89.76
21	-1.26356	36.80106	23	1713.8	322	1526640867	0.8	6.39	0.83	6	0.1	3	0.28	18.49	16.68
22	-1.26344	36.80075	28	1718.8	317	1526640872	0.8	7.78	1.39	-5	5	5	0.28	22.05	31.95
23	-1.26303	36.80043	36	1724.6	318	1526640878	0.8	10	2.22	1	5.8	6	0.37	28.45	46.68
24	-1.26224	36.79978	45	1717.5	308	1526640887	0.8	12.5	2.5	-10	-7.1	9	0.28	39.89	90
25	-1.26197	36.79936	51	1717.2	298	1526640891	0.8	14.17	1.67	-10	-0.3	4	0.42	54.50	50
26	-1.26139	36.79764	40	1726.6	280	1526640906	0.9	11.11	-3.06	-18	9.4	15	-0.2	65.28	212.55
27	-1.26132	36.79723	3	1721.8	285	1526640919	0.8	0.83	-10.28	5	-4.8	13	-0.79	46.15	144.43
28	-1.2613	36.79717	6	1721.2	281	1526640923	0.8	1.67	0.84	-4	-0.6	4	0.21	2.19	3.32
29	-1.26129	36.79705	5	1720.4	274	1526640930	0.8	1.39	-0.28	-7	-0.8	7	-0.04	4.58	11.69
30	-1.26129	36.79691	4	1719.8	264	1526640937	0.8	1.11	-0.28	-10	-0.6	7	-0.04	3.76	9.73
31	-1.26124	36.79643	6	1727.8	282	1526640951	0.8	1.67	0.56	18	8	14	0.04	2.96	15.54
32	-1.26122	36.79625	6	1727.3	279	1526640957	0.8	1.67	0	-3	-0.5	6	0	4.58	10.02
33	-1.2612	36.7961	5	1730.1	273	1526640967	0.8	1.39	-0.28	-6	2.8	10	-0.03	4.58	16.7
34	-1.26117	36.79595	8	1732.8	282	1526640973	0.8	2.22	0.83	9	2.7	6	0.14	3.76	8.34
35	-1.26114	36.79579	11	1733.2	275	1526640977	0.8	3.06	0.84	-7	0.4	4	0.21	6.29	8.88
36	-1.26108	36.79549	6	1733.9	284	1526640987	0.8	1.67	-1.39	9	0.7	10	-0.14	9.03	30.6
37	-1.26106	36.79538	6	1734.2	287	1526640991	0.8	1.67	0	3	0.3	4	0	4.58	6.68
38	-1.26105	36.79519	8	1735.4	274	1526640997	0.8	2.22	0.55	-13	1.2	6	0.09	4.58	10.02
39	-1.26091	36.79363	5	1724.4	281	1526641076	0.8	1.39	-0.83	7	-11	79	-0.01	6.29	175.38
40	-1.26089	36.7934	7	1726.3	281	1526641086	0.8	1.94	0.55	0	1.9	10	0.06	3.76	13.9
41	-1.26086	36.79311	8	1726.5	276	1526641098	0.8	2.22	0.28	-5	0.2	12	0.02	5.43	23.28
42	-1.26081	36.79269	17	1727.9	278	1526641107	0.8	4.72	2.5	2	1.4	9	0.28	6.29	19.98
43	-1.26078	36.7925	11	1728.5	280	1526641112	0.8	3.06	-1.66	2	0.6	5	-0.33	15.13	23.6
44	-1.26074	36.79234	14	1728.8	283	1526641117	0.8	3.89	0.83	3	0.3	5	0.17	9.03	15.3
45	-1.26069	36.79204	3	1728.8	275	1526641131	0.8	0.83	-3.06	-8	0	14	-0.22	11.98	54.46
46	-1.26068	36.79193	7	1728.7	277	1526641137	0.8	1.94	1.11	2	-0.1	6	0.19	2.19	4.98
47	-1.26059	36.79164	2	1732.1	319	1526641149	0.8	0.56	-1.38	42	3.4	12	-0.12	5.43	23.28
48	-1.26054	36.7915	8	1735.3	289	1526641158	0.8	2.22	1.66	-30	3.2	9	0.18	1.44	5.04
49	-1.26055	36.79132	7	1740.1	293	1526641167	0.8	1.94	-0.28	4	4.8	9	-0.03	6.29	19.98
50	-1.2605	36.79096	23	1740.5	282	1526641173	0.8	6.39	4.45	-11	0.4	6	0.74	5.43	11.64
51	-1.26043	36.79076	19	1742.8	284	1526641177	0.9	5.28	-1.11	2	2.3	4	-0.28	22.05	25.56
52	-1.26016	36.78961	45	1745.9	279	1526641191	0.8	12.5	7.22	-5	3.1	14	0.52	17.35	73.92
53	-1.26009	36.78911	47	1751.9	278	1526641195	0.8	13.06	0.56	-1	6	4	0.14	54.50	50
54	-1.26003	36.78862	50	1752.2	276	1526641199	0.8	13.89	0.83	-2	0.3	4	0.21	58.00	52.24
55	-1.25998	36.78811	48	1753.2	276	1526641203	0.8	13.33	-0.56	0	1	4	-0.14	63.43	55.56
56	-1.25992	36.78756	55	1754.7	276	1526641207	0.8	15.28	1.95	0	1.5	4	0.49	59.79	53.32
57	-1.25986	36.78699	52	1754.9	275	1526641211	0.8	14.44	-0.84	-1	0.2	4	-0.21	72.92	61.12
58	-1.25969	36.78544	26	1756.8	278	1526641226	0.8	7.22	-7.22	3	1.9	15	-0.48	67.16	216.6
59	-1.25961	36.78495	9	1755.6	286	1526641236	0.8	2.5	-4.72	8	-1.2	10	-0.47	25.82	72.2
60	-1.2596	36.78482	11	1755.7	276	1526641240	0.8	3.06	0.56	-10	0.1	4	0.14	7.18	10
61	-1.25946	36.78368	30	1761	277	1526641259	0.8	8.33	5.27	1	5.3	19	0.28	9.03	58.14
62	-1.25949	36.78311	14	1782.8	261	1526641266	0.9	3.89	-4.44	-16	21.8	7	-0.63	31.17	58.31
63	-1.25934	36.78234	28	1778.5	278	1526641275	0.8	7.78	3.89	17	-4.3	9	0.43	11.98	35.01
64	-1.25925	36.78187	17	1774.4	276	1526641282	0.8	4.72	-3.06	-2	-4.1	7	-0.44	28.45	54.46
65	-1.25919	36.78139	21	1770.8	277	1526641292	0.8	5.83	1.11	1	-3.6	10	0.11	15.13	47.2
66	-1.25915	36.78084	12	1771.8	279	1526641306	0.8	3.33	-2.5	2	1	14	-0.18	19.65	81.62
67	-1.25911	36.78039	15	1774.3	276	1526641315	0.8	4.17	0.84	-3	2.5	9	0.09	9.99	29.97
68	-1.25903	36.78002	19	1773.4	275	1526641325	0.8	5.28	1.11	-1	-0.9	10	0.11	13.01	41.7
69	-1.259	36.77976	26	1773.2	276	1526641329	0.8	7.22	1.94	1	-0.2	4	0.49	17.35	21.12
70	-1.25899	36.7794	16	1772.5	271	1526641335	0.8	4.44	-2.78	-5	-0.7	6	-0.46	25.82	43.32
71	-1.25901	36.77928	8	1772.8	269	1526641339	0.8	2.22	-2.22	-2	0.3	4	-0.56	14.06	17.76
72	-1.25903	36.77926	5	1777.1	270	1526641345	0.8	1.39	-0.83	1	4.3	6	-0.14	6.29	13.32
73	-1.25901	36.77898	17	1777.1	268	1526641355	0.8	4.72	3.33	-2	0	10	0.33	3.76	13.9

74	-1.26031	36.77136	49	1784.3	258	1526641436	0.8	13.61	8.89	-10	7.2	81	0.11	15.13	382.32
75	-1.2606	36.77006	53	1789.1	257	1526641446	0.8	14.72	1.11	-1	4.8	10	0.11	61.60	136.1
76	-1.26087	36.76882	59	1793.7	257	1526641455	0.9	16.39	1.67	0	4.6	9	0.19	69.06	132.48
77	-1.26103	36.76822	64	1794	253	1526641459	0.9	17.78	1.39	-4	0.3	4	0.35	80.93	65.56
78	-1.26126	36.7676	68	1794.4	246	1526641463	0.9	18.89	1.11	-7	0.4	4	0.28	91.46	71.12
79	-1.26164	36.76699	72	1794.4	236	1526641467	0.9	20	1.11	-10	0	4	0.28	100.30	75.56
80	-1.26207	36.7664	73	1795.1	235	1526641471	0.8	20.28	0.28	-1	0.7	4	0.07	109.50	80
81	-1.2625	36.7658	73	1796.1	236	1526641475	0.8	20.28	0	1	1	4	0	111.86	81.12
82	-1.26287	36.76516	74	1796.6	243	1526641479	0.8	20.56	0.28	7	0.5	4	0.07	111.86	81.12
83	-1.26344	36.76268	72	1801.4	259	1526641493	0.8	20	-0.56	16	4.8	14	-0.04	114.24	287.84
84	-1.26357	36.76201	68	1802	259	1526641497	0.8	18.89	-1.11	0	0.6	4	-0.28	109.50	80
85	-1.26368	36.76139	61	1805.1	261	1526641501	0.8	16.94	-1.95	2	3.1	4	-0.49	100.30	75.56
86	-1.26377	36.76082	57	1808.3	262	1526641505	0.8	15.83	-1.11	1	3.2	4	-0.28	85.08	67.76
87	-1.26385	36.76023	61	1810.7	263	1526641509	0.8	16.94	1.11	1	2.4	4	0.28	76.88	63.32
88	-1.26391	36.75959	65	1811.3	265	1526641513	0.8	18.06	1.12	2	0.6	4	0.28	85.08	67.76
89	-1.26395	36.75892	66	1811.7	267	1526641517	0.8	18.33	0.27	2	0.4	4	0.07	93.64	72.24
90	-1.26401	36.75825	67	1812.3	264	1526641521	0.8	18.61	0.28	-3	0.6	4	0.07	95.84	73.32
91	-1.26408	36.75758	67	1814	263	1526641525	0.8	18.61	0	-1	1.7	4	0	98.06	74.44
92	-1.26416	36.75692	66	1816.7	265	1526641529	0.8	18.33	-0.28	2	2.7	4	-0.07	98.06	74.44
93	-1.26422	36.75631	59	1818.5	267	1526641533	0.8	16.39	-1.94	2	1.8	4	-0.48	95.84	73.32
94	-1.26424	36.75571	63	1819.1	268	1526641537	0.8	17.5	1.11	1	0.6	4	0.28	80.93	65.56
95	-1.26431	36.75383	48	1819.9	270	1526641551	0.8	13.33	-4.17	2	0.8	14	-0.3	89.31	245
96	-1.26429	36.75308	41	1820.3	271	1526641558	0.8	11.39	-1.94	1	0.4	7	-0.28	59.79	93.31
97	-1.26429	36.75255	42	1821	271	1526641563	0.8	11.67	0.28	0	0.7	5	0.06	47.78	56.95
98	-1.26427	36.75201	45	1822.7	270	1526641568	0.8	12.5	0.83	-1	1.7	5	0.17	49.42	58.35
99	-1.26428	36.75152	51	1823.2	271	1526641572	0.8	14.17	1.67	1	0.5	4	0.42	54.50	50
100	-1.26426	36.75096	58	1825.5	272	1526641576	0.8	16.11	1.94	1	2.3	4	0.49	65.28	56.68
101	-1.26426	36.75035	61	1828.4	268	1526641580	0.8	16.94	0.83	-4	2.9	4	0.21	78.90	64.44
102	-1.26429	36.7497	65	1830.5	268	1526641584	0.8	18.06	1.12	0	2.1	4	0.28	85.08	67.76
103	-1.26432	36.74903	66	1832.6	268	1526641588	0.8	18.33	0.27	0	2.1	4	0.07	93.64	72.24
104	-1.26432	36.74837	64	1834.5	269	1526641592	0.8	17.78	-0.55	1	1.9	4	-0.14	95.84	73.32
105	-1.26434	36.74775	60	1836.5	268	1526641596	0.8	16.67	-1.11	-1	2	4	-0.28	91.46	71.12
106	-1.26475	36.73675	60	1866	269	1526641682	0.8	16.67	0	1	29.5	86	0	82.99	1433.62
107	-1.26468	36.73537	59	1870.1	278	1526641691	0.8	16.39	-0.28	9	4.1	9	-0.03	82.99	150.03
108	-1.26462	36.73481	56	1870.6	276	1526641695	0.8	15.56	-0.83	-2	0.5	4	-0.21	80.93	65.56
109	-1.26453	36.73426	57	1872.5	279	1526641699	0.8	15.83	0.27	3	1.9	4	0.07	74.89	62.24
110	-1.26444	36.73368	59	1873.1	279	1526641703	0.8	16.39	0.56	0	0.6	4	0.14	76.88	63.32
111	-1.26437	36.73301	67	1873.7	276	1526641707	0.8	18.61	2.22	-3	0.6	4	0.56	80.93	65.56
112	-1.26417	36.73155	74	1874.1	277	1526641715	0.8	20.56	1.95	1	0.4	8	0.24	98.06	148.88
113	-1.26406	36.73083	70	1873.9	279	1526641719	0.8	19.44	-1.12	2	-0.2	4	-0.28	114.24	82.24
114	-1.26349	36.72872	60	1876.7	292	1526641733	0.8	16.67	-2.77	13	2.8	14	-0.2	104.86	272.16
115	-1.26323	36.72817	59	1876.9	297	1526641737	0.8	16.39	-0.28	5	0.2	4	-0.07	82.99	66.68
116	-1.26264	36.72711	59	1878	302	1526641745	0.8	16.39	0	5	1.1	8	0	80.93	131.12
117	-1.26234	36.72663	53	1879.1	304	1526641749	0.8	14.72	-1.67	2	1.1	4	-0.42	80.93	65.56
118	-1.26203	36.72619	51	1880.7	305	1526641753	0.8	14.17	-0.55	1	1.6	4	-0.14	69.06	58.88
119	-1.26173	36.72567	59	1881.3	299	1526641757	0.8	16.39	2.22	-6	0.6	4	0.56	65.28	56.68
120	-1.26142	36.72509	64	1882.6	298	1526641761	0.8	17.78	1.39	-1	1.3	4	0.35	80.93	65.56
121	-1.26113	36.72452	62	1885.3	297	1526641765	0.8	17.22	-0.56	-1	2.7	4	-0.14	91.46	71.12
122	-1.2609	36.7239	66	1888.6	290	1526641769	0.8	18.33	1.11	-7	3.3	4	0.28	87.18	68.88
123	-1.2607	36.72327	66	1890.7	287	1526641773	0.8	18.33	0	-3	2.1	4	0	95.84	73.32
124	-1.26052	36.72267	62	1891.9	285	1526641777	0.8	17.22	-1.11	-2	1.2	4	-0.28	95.84	73.32
125	-1.26028	36.72022	74	1901	270	1526641791	0.8	20.56	3.34	-15	9.1	14	0.24	87.18	241.08
126	-1.26032	36.71945	76	1901.2	266	1526641795	0.8	21.11	0.55	-4	0.2	4	0.14	114.24	82.24
127	-1.26042	36.71869	76	1902.2	261	1526641799	0.8	21.11	0	-5	1	4	0	119.07	84.44
128	-1.26057	36.71795	74	1903.9	259	1526641803	0.8	20.56	-0.55	-2	1.7	4	-0.14	119.07	84.44
129	-1.26072	36.71724	70	1906.5	258	1526641807	0.8	19.44	-1.12	-1	2.6	4	-0.28	114.24	82.24
130	-1.26087	36.71662	62	1908.8	258	1526641811	0.8	17.22	-2.22	0	2.3	4	-0.56	104.86	77.76
131	-1.26098	36.71599	65	1910.5	261	1526641815	0.8	18.06	0.84	3	1.7	4	0.21	87.18	68.88
132	-1.26106	36.71532	69	1911.5	265	1526641819	0.8	19.17	1.11	4	1	4	0.28	93.64	72.24
133	-1.26072	36.71247	73	1912.3	280	1526641835	0.8	20.28	1.11	15	0.8	16	0.07	102.57	306.72
134	-1.26006	36.70875	67	1920.6	280	1526641857	0.8	18.61	-1.67	0	8.3	22	-0.08	111.86	446.16
135	-1.25976	36.70685	73	1922.3	280	1526641868	0.8	20.28	1.67	0	1.7	11	0.15	98.06	204.71
136	-1.25936	36.70524	72	1925.8	286	1526641877	0.8	20	-0.28	6	3.5	9	-0.03	111.86	182.52
137	-1.25914	36.70453	75	1926.2	288	1526641881	0.8	20.83	0.83	2	0.4	4	0.21	109.50	80
138	-1.25813	36.70166	76	1934	290	1526641897	0.8	21.11	0.28	2	7.8	16	0.02	116.65	333.28
139	-1.25725	36.6992	77	1937.9	289	1526641911	0.8	21.39	0.28	-1	3.9	14	0.02	119.07	295.54
140	-1.257	36.69849	75	1938.3	289	1526641915	0.8	20.83	-0.56	0	0.4	4	-0.14	121.52	85.56
141	-1.25599	36.69563	78	1946.8	290	1526641931	0.8	21.67	0.84	1	8.5	16	0.05	116.65	333.28
142	-1.25575	36.69495	69	1949	289	1526641935	0.8	19.17	-2.5	-1	2.2	4	-0.63	124.00	86.68
143	-1.25556	36.69439	56	1950.3	289	1526641939	0.8	15.56	-3.61	0	1.3	4	-0.9	102.57	76.68
144	-1.25539	36.69391	51	1950.6	289	1526641943	0.8	14.17	-1.39	0	0.3	4	-0.35	74.89	62.24
145	-1.25523	36.69344	52	1950.8	290	1526641947	0.8	14.44	0.27	1	0.2	4	0.07	65.28	56.68
146	-1.25504	36.69292	56	1950.3	289	1526641951	0.8	15.56	1.12	-1	-0.5	4	0.28	67.16	57.76
147	-1.25485	36.6924	56	1949.5	289	1526641955	0.8	15.56	0	0	-0.8	4	0	74.89	62.24
148	-1.25338	36.68976	73	1951.5	304	1526641973	0.8	20.28	4.72	15	2	18	0.26	74.89	280.08
149	-1.25294	36.68914	76	1953.2	305	1526641977	0.8	21.11	0.83	1	1.7	4	0.21	111.86	81.12
150	-1.25182	36.68756	78	1956.3	305	1526641987	0.8	21.67	0.56	0	3.1	10	0.06	119.07	211.1
151	-1.25038	36.68552	75	1958.1	305	1526642000	0.8	20.83	-0.84	0	1.8	13	-0.06	124.00	281.71
152	-1.24996	36.68493	70	1958.8	304	1526642004	0.8	19.44	-1.39	-1	0.7	4	-0.35	116.65	83.32
153	-1.24957	36.68438	68	1959.6	306	1526642008	0.8	18.89	-0.55	2	0.8	4	-0.14	104.86	77.76
154	-1.24918	36.68383	68	1960.2	305	1526642012	0.8	18.89	0	-1	0.6	4	0	100.30	75.56
155	-1.2488	36.68329	66	1961.2	305	1526642016	0.8	18.33	-0.56	0	1	4	-0.14	100.30	75.56
156	-1.24843	36.68276	66	1962.3	305	1526642020	0.8	18.33	0	0	1.1	4	0	95.84	73.32
157	-1.24719	36.68095	64	1964.5	307	1526642034	0.8	17.78	-0.55	2	2.2	14	-0.04	95.84	256.62

158	-1.24676	36.68045	67	1964.8	312	1526642038	0.8	18.61	0.83	5	0.3	4	0.21	91.46	71.12
159	-1.24631	36.68	63	1966.1	315	1526642042	0.8	17.5	-1.11	3	1.3	4	-0.28	98.06	74.44
160	-1.24586	36.67959	61	1967.7	318	1526642046	0.8	16.94	-0.56	3	1.6	4	-0.14	89.31	70
161	-1.2454	36.67918	63	1969.8	320	1526642050	0.8	17.5	0.56	2	2.1	4	0.14	85.08	67.76
162	-1.24446	36.67835	61	1975.6	319	1526642058	0.8	16.94	-0.56	-1	5.8	8	-0.07	89.31	140
163	-1.24394	36.67793	28	1980	318	1526642065	0.8	7.78	-9.16	-1	4.4	7	-1.31	85.08	118.58
164	-1.24357	36.67766	19	1981.6	320	1526642078	0.8	5.28	-2.5	2	1.6	13	-0.19	28.45	101.14
165	-1.24252	36.67675	25	1980.9	319	1526642099	0.8	6.94	1.66	-1	-0.7	21	0.08	17.35	110.88
166	-1.2422	36.67649	24	1982.3	324	1526642106	0.8	6.67	-0.27	5	1.4	7	-0.04	24.54	48.58
167	-1.24187	36.67627	34	1982.1	328	1526642111	0.8	9.44	2.77	4	-0.2	5	0.55	23.29	33.35
168	-1.24145	36.67602	38	1981.9	332	1526642116	0.9	10.56	1.12	4	-0.2	5	0.22	36.89	47.2
169	-1.24103	36.67579	38	1982.5	332	1526642121	0.8	10.56	0	0	0.6	5	0	42.97	52.8
170	-1.24059	36.67555	40	1984.4	332	1526642126	0.8	11.11	0.55	0	1.9	5	0.11	42.97	52.8
171	-1.24013	36.67531	43	1987.1	332	1526642131	0.8	11.94	0.83	0	2.7	5	0.17	46.15	55.55
172	-1.23969	36.67508	51	1987.6	332	1526642135	0.8	14.17	2.23	0	0.5	4	0.56	51.09	47.76
173	-1.23918	36.67482	57	1990.4	332	1526642139	0.8	15.83	1.66	0	2.8	4	0.42	65.28	56.68
174	-1.23709	36.67371	76	1995.4	332	1526642153	0.8	21.11	5.28	0	5	14	0.38	76.88	221.62
175	-1.23644	36.67332	78	1995.8	326	1526642157	0.8	21.67	0.56	-6	0.4	4	0.14	119.07	84.44
176	-1.23585	36.67282	78	1997.9	314	1526642161	0.8	21.67	0	-12	2.1	4	0	124.00	86.68
177	-1.23535	36.67222	77	2001.1	307	1526642165	0.8	21.39	-0.28	-7	3.2	4	-0.07	124.00	86.68
178	-1.2349	36.6716	76	2005.4	305	1526642169	0.8	21.11	-0.28	-2	4.3	4	-0.07	121.52	85.56
179	-1.23406	36.67041	69	2014.8	305	1526642177	0.8	19.17	-1.94	0	9.4	8	-0.24	119.07	168.88
180	-1.23369	36.66987	64	2019.2	305	1526642181	0.8	17.78	-1.39	0	4.4	4	-0.35	102.57	76.68
181	-1.23333	36.66937	61	2023.2	304	1526642185	0.8	16.94	-0.84	-1	4	4	-0.21	91.46	71.12
182	-1.23296	36.66893	59	2027.5	315	1526642189	0.8	16.39	-0.55	11	4.3	4	-0.14	85.08	67.76
183	-1.23252	36.66855	58	2031.8	323	1526642193	0.8	16.11	-0.28	8	4.3	4	-0.07	80.93	65.56
184	-1.23204	36.66826	58	2035.5	332	1526642197	0.8	16.11	0	9	3.7	4	0	78.90	64.44
185	-1.22534	36.66379	26	2064.8	354	1526642273	0.8	7.22	-8.89	22	29.3	76	-0.12	78.90	1224.36
186	-1.22429	36.66365	49	2070.9	350	1526642284	0.8	13.61	6.39	-4	6.1	11	0.58	25.82	79.42
187	-1.22295	36.66346	65	2071.1	352	1526642293	0.8	18.06	4.45	2	0.2	9	0.49	61.60	122.49
188	-1.22224	36.66336	72	2075.6	353	1526642297	0.8	20	1.94	1	4.5	4	0.49	93.64	72.24
189	-1.22148	36.66325	77	2078.3	352	1526642301	0.8	21.39	1.39	-1	2.7	4	0.35	109.50	80
190	-1.22069	36.66315	78	2081.1	353	1526642305	0.8	21.67	0.28	1	2.8	4	0.07	121.52	85.56
191	-1.21989	36.66304	79	2082.4	352	1526642309	0.8	21.94	0.27	-1	1.3	4	0.07	124.00	86.68
192	-1.21909	36.66291	77	2082.9	352	1526642313	0.8	21.39	-0.55	0	0.5	4	-0.14	126.49	87.76
193	-1.21843	36.66281	60	2083	352	1526642317	0.8	16.67	-4.72	0	0.1	4	-1.18	121.52	85.56
194	-1.21633	36.66256	69	2084.7	351	1526642331	0.9	19.17	2.5	-1	1.7	14	0.18	82.99	233.38
195	-1.21565	36.6624	69	2084.5	345	1526642335	0.9	19.17	0	-6	-0.2	4	0	102.57	76.68
196	-1.215	36.66212	69	2081.4	332	1526642339	0.9	19.17	0	-13	-3.1	4	0	102.57	76.68
197	-1.21446	36.66174	66	2078.1	320	1526642343	0.9	18.33	-0.84	-12	-3.3	4	-0.21	102.57	76.68
198	-1.21402	36.66128	63	2075.1	312	1526642347	0.9	17.5	-0.83	-8	-3	4	-0.21	95.84	73.32
199	-1.21361	36.66078	65	2073.1	309	1526642351	0.8	18.06	0.56	-3	-2	4	0.14	89.31	70
200	-1.21321	36.66028	62	2073.3	308	1526642355	0.8	17.22	-0.84	-1	0.2	4	-0.21	93.64	72.24
201	-1.21281	36.65979	65	2074.2	311	1526642359	0.8	18.06	0.84	3	0.9	4	0.21	87.18	68.88
202	-1.21231	36.65933	70	2075.3	323	1526642363	0.8	19.44	1.38	12	1.1	4	0.35	93.64	72.24
203	-1.21169	36.65897	73	2076	333	1526642367	0.8	20.28	0.84	10	0.7	4	0.21	104.86	77.76
204	-1.21101	36.65867	74	2077.5	337	1526642371	0.8	20.56	0.28	4	1.5	4	0.07	111.86	81.12
205	-1.21031	36.65839	75	2080.4	338	1526642375	0.8	20.83	0.27	1	2.9	4	0.07	114.24	82.24
206	-1.20959	36.6581	77	2084.1	338	1526642379	0.8	21.39	0.56	0	3.7	4	0.14	116.65	83.32
207	-1.20693	36.65703	83	2092.7	338	1526642393	0.8	23.06	1.67	0	8.6	14	0.12	121.52	299.46
208	-1.20617	36.65672	81	2093	338	1526642397	0.8	22.5	-0.56	0	0.3	4	-0.14	136.71	92.24
209	-1.20542	36.65641	81	2093.3	338	1526642401	0.8	22.5	0	0	0.3	4	0	131.55	90
210	-1.20466	36.6561	82	2093.3	338	1526642405	0.8	22.78	0.28	0	0	4	0.07	131.55	90
211	-1.20389	36.65578	81	2093.5	338	1526642409	0.8	22.5	-0.28	0	0.2	4	-0.07	134.12	91.12
212	-1.20316	36.65549	78	2093.5	338	1526642413	0.8	21.67	-0.83	0	0	4	-0.21	131.55	90
213	-1.20247	36.65521	73	2092.9	338	1526642417	0.8	20.28	-1.39	0	-0.6	4	-0.35	124.00	86.68
214	-1.20181	36.65494	72	2092.3	338	1526642421	0.8	20	-0.28	0	-0.6	4	-0.07	111.86	81.12
215	-1.20113	36.65467	74	2092.1	337	1526642425	0.8	20.56	0.56	-1	-0.2	4	0.14	109.50	80
216	-1.20043	36.65439	75	2093	338	1526642429	0.8	20.83	0.27	1	0.9	4	0.07	114.24	82.24
217	-1.19972	36.6541	77	2094.9	338	1526642433	0.8	21.39	0.56	0	1.9	4	0.14	116.65	83.32
218	-1.19901	36.65382	76	2097.3	337	1526642437	0.8	21.11	-0.28	-1	2.4	4	-0.07	121.52	85.56
219	-1.1983	36.65353	75	2100.2	338	1526642441	0.8	20.83	-0.28	1	2.9	4	-0.07	119.07	84.44
220	-1.19577	36.65249	45	2103.4	335	1526642459	0.8	12.5	-8.33	-3	3.2	18	-0.46	116.65	374.94
221	-1.19397	36.65141	38	2127	325	1526642480	0.8	10.56	-1.94	-10	23.6	21	-0.09	54.50	262.5
222	-1.19319	36.65085	40	2130.3	323	1526642489	0.8	11.11	0.55	-2	3.3	9	0.06	42.97	95.04
223	-1.19276	36.65054	17	2131.5	324	1526642496	0.8	4.72	-6.39	1	1.2	7	-0.91	46.15	77.77
224	-1.19263	36.65045	17	2132	325	1526642500	0.8	4.72	0	1	0.5	4	0	15.13	18.88
225	-1.19181	36.64991	42	2129.2	328	1526642514	0.8	11.67	6.95	3	-2.8	14	0.5	15.13	66.08
226	-1.19137	36.64963	53	2129	329	1526642518	0.8	14.72	3.05	1	-0.2	4	0.76	49.42	46.68
227	-1.19083	36.64932	64	2129.7	330	1526642522	0.8	17.78	3.06	1	0.7	4	0.77	69.06	58.88
228	-1.19021	36.649	71	2131.3	334	1526642526	0.8	19.72	1.94	4	1.6	4	0.48	91.46	71.12
229	-1.18954	36.64867	72	2132.4	333	1526642530	0.8	20	0.28	-1	1.1	4	0.07	107.17	78.88
230	-1.18889	36.64833	70	2133	335	1526642534	0.8	19.44	-0.56	2	0.6	4	-0.14	109.50	80
231	-1.18827	36.64805	68	2133.4	333	1526642538	0.8	18.89	-0.55	-2	0.4	4	-0.14	104.86	77.76
232	-1.18763	36.64771	74	2133.5	333	1526642542	0.8	20.56	1.67	0	0.1	4	0.42	100.30	75.56
233	-1.18691	36.64737	81	2133	334	1526642546	0.8	22.5	1.94	1	-0.5	4	0.49	114.24	82.24
234	-1.18617	36.64701	81	2132	334	1526642550	0.8	22.5	0	0	-1	4	0	131.55	90
235	-1.18544	36.64665	81	2131	334	1526642554	0.8	22.5	0	0	-1	4	0	131.55	90
236	-1.18472	36.64631	79	2130.5	334	1526642558	0.8	21.94	-0.56	0	-0.5	4	-0.14	131.55	90
237	-1.17534	36.64217	48	2172.9	352	1526642631	0.8	13.33	-8.61	18	42.4	73	-0.12	126.49	1601.62
238	-1.17338	36.64188	65	2180.5	351	1526642644	0.8	18.06	4.73	-1	7.6	13	0.36	59.79	173.29
239	-1.17202	36.64166	55	2185.5	351	1526642653	0.8	15.28	-2.78	0	5	9	-0.31	93.64	162.54
240	-1.17145	36.64157	58	2186	351	1526642657	0.8	16.11	0.83	0	0.5	4	0.21	72.92	61.12
241	-1.17089	36.64148	56	2188.2	350	1526642661	0.8	15.56	-0.55	-1	2.2	4	-0.14	78.90	64.44

242	-1.17038	36.6414	50	2190.4	351	1526642665	0.8	13.89	-1.67	1	2.2	4	-0.42	74.89	62.24
243	-1.16986	36.64131	54	2192.2	351	1526642669	0.8	15	1.11	0	1.8	4	0.28	63.43	55.56
244	-1.16868	36.64111	63	2196.6	351	1526642677	0.8	17.5	2.5	0	4.4	8	0.31	70.98	120
245	-1.16803	36.64101	66	2199.4	350	1526642681	0.8	18.33	0.83	-1	2.8	4	0.21	89.31	70
246	-1.16563	36.64062	69	2209.5	351	1526642695	0.8	19.17	0.84	1	10.1	14	0.06	95.84	256.62
247	-1.16495	36.64051	69	2210.1	351	1526642699	0.8	19.17	0	0	0.6	4	0	102.57	76.68
248	-1.16434	36.64042	60	2212.7	350	1526642703	0.8	16.67	-2.5	-1	2.6	4	-0.63	102.57	76.68
249	-1.16376	36.64032	61	2215.7	350	1526642707	0.8	16.94	0.27	0	3	4	0.07	82.99	66.68
250	-1.16249	36.6401	65	2222	348	1526642715	0.8	18.06	1.12	-2	6.3	8	0.14	85.08	135.52
251	-1.16182	36.63997	69	2224.4	350	1526642719	0.8	19.17	1.11	2	2.4	4	0.28	93.64	72.24
252	-1.1611	36.63984	74	2226.4	351	1526642723	0.8	20.56	1.39	1	2	4	0.35	102.57	76.68
253	-1.16034	36.63973	76	2227.4	352	1526642727	0.8	21.11	0.55	1	1	4	0.14	114.24	82.24
254	-1.15956	36.63961	79	2227.7	351	1526642731	0.8	21.94	0.83	-1	0.3	4	0.21	119.07	84.44
255	-1.15875	36.63947	81	2227.6	351	1526642735	0.8	22.5	0.56	0	-0.1	4	0.14	126.49	87.76
256	-1.15794	36.63935	82	2228.2	352	1526642739	0.8	22.78	0.28	1	0.6	4	0.07	131.55	90
257	-1.15515	36.63886	81	2234.7	350	1526642753	0.8	22.5	-0.28	-2	6.5	14	-0.02	134.12	318.92
258	-1.15438	36.63873	75	2234.9	350	1526642757	0.8	20.83	-1.67	0	0.2	4	-0.42	131.55	90
259	-1.15373	36.63862	63	2236.8	351	1526642761	0.8	17.5	-3.33	1	1.9	4	-0.83	116.65	83.32
260	-1.15326	36.63856	44	2239.8	352	1526642765	0.8	12.22	-5.28	1	3	4	-1.32	89.31	70
261	-1.15274	36.63849	27	2245.3	351	1526642772	0.8	7.5	-4.72	-1	5.5	7	-0.67	52.79	85.54
262	-1.15227	36.63842	27	2247.3	350	1526642779	0.9	7.5	0	-1	2	7	0	27.13	52.5
263	-1.1518	36.63834	29	2248.7	350	1526642786	0.8	8.06	0.56	0	1.4	7	0.08	27.13	52.5
264	-1.15134	36.63827	32	2247.4	351	1526642792	0.8	8.89	0.83	1	-1.3	6	0.14	29.80	48.36
265	-1.15087	36.63818	29	2248	351	1526642798	0.8	8.06	-0.83	0	0.6	6	-0.14	33.99	53.34
266	-1.14345	36.63696	24	2263.8	349	1526642877	0.8	6.67	-1.39	-2	15.8	79	-0.02	29.80	636.74
267	-1.14262	36.63683	24	2265.8	352	1526642889	0.8	6.67	0	3	2	12	0	23.29	80.04
268	-1.14208	36.63675	30	2266.8	351	1526642898	0.8	8.33	1.66	-1	1	9	0.18	23.29	60.03
269	-1.14154	36.63667	32	2266.9	350	1526642905	0.8	8.89	0.56	-1	0.1	7	0.08	31.17	58.31
270	-1.14122	36.63661	34	2267.2	350	1526642909	0.8	9.44	0.55	0	0.3	4	0.14	33.99	35.56
271	-1.14083	36.63654	42	2267.7	349	1526642913	0.8	11.67	2.23	-1	0.5	4	0.56	36.89	37.76
272	-1.14033	36.63646	52	2267.3	349	1526642917	0.8	14.44	2.77	0	-0.4	4	0.69	49.42	46.68
273	-1.13977	36.63635	58	2267.5	349	1526642921	0.8	16.11	1.67	0	0.2	4	0.42	67.16	57.76
274	-1.13747	36.63592	76	2276.7	349	1526642935	0.8	21.11	5	0	9.2	14	0.36	78.90	225.54
275	-1.13677	36.63578	72	2277.2	349	1526642939	0.8	20	-1.11	0	0.5	4	-0.28	119.07	84.44
276	-1.13614	36.63566	61	2279.2	348	1526642943	0.8	16.94	-3.06	-1	2	4	-0.77	109.50	80
277	-1.13563	36.63556	49	2281.1	348	1526642947	0.8	13.61	-3.33	0	1.9	4	-0.83	85.08	67.76
278	-1.13515	36.63545	10	2285.5	346	1526642956	0.8	2.78	-10.83	-2	4.4	9	-1.2	61.60	122.49
279	-1.13497	36.63541	0	2286.4	347	1526642968	0.8	0	-2.78	1	0.9	12	-0.23	8.10	33.36
280	-1.1348	36.63537	17	2287	347	1526642978	0.8	4.72	4.72	0	0.6	10	0.47	0.00	0
281	-1.13455	36.63531	26	2285.1	348	1526642983	0.8	7.22	2.5	1	-1.9	5	0.5	15.13	23.6
282	-1.13331	36.63503	41	2284	347	1526642997	0.8	11.39	4.17	-1	-1.1	14	0.3	25.82	101.08

Table 0.13. Driver D4 of the Public Service Vehicle Category

	Lat	Lon	Speed (km/h)	Altitude	Direction (Angle Changes)	GPSTime	GPS Signal Strength	Speed (m/s)	Change in Speed (m/s)	Change in Direction	Change in Altitude	Change in Time (s)	Accl/Decl (m/s^2)	SSD Based on Initial Speed (m)	Actual Distance to Stop (m)
1	-1.27372	36.81037	51	1683.5	334	1529133427	1.3	14.17							
2	-1.27336	36.80998	54	1685.4	304	1529133431	1.3	15	0.83	-30	1.9	4	0.21	65.28	56.68
3	-1.27307	36.80953	54	1687.8	305	1529133435	1.3	15	0	1	2.4	4	0	70.98	60
4	-1.2727	36.80909	57	1687.5	310	1529133439	1.3	15.83	0.83	5	-0.3	4	0.21	70.98	60
5	-1.27234	36.80867	54	1687.8	313	1529133443	1.3	15	-0.83	3	0.3	4	-0.21	76.88	63.32
6	-1.27193	36.80827	60	1690.1	317	1529133447	1.3	16.67	1.67	4	2.3	4	0.42	70.98	60
7	-1.27146	36.80783	65	1693.6	317	1529133451	1.3	18.06	1.39	0	3.5	4	0.35	82.99	66.68
8	-1.26993	36.80646	68	1693.9	321	1529133463	1.3	18.89	0.83	4	0.3	12	0.07	93.64	216.72
9	-1.26943	36.80604	63	1695.6	317	1529133467	1.3	17.5	-1.39	-4	1.7	4	-0.35	100.30	75.56
10	-1.26897	36.80562	63	1699.2	319	1529133471	1.3	17.5	0	2	3.6	4	0	89.31	70
11	-1.26846	36.80517	66	1702.5	318	1529133475	1.3	18.33	0.83	-1	3.3	4	0.21	89.31	70
12	-1.26668	36.80366	68	1700	320	1529133489	1.3	18.89	0.56	2	-2.5	14	0.04	95.84	256.62
13	-1.26614	36.8032	72	1699.9	319	1529133493	1.3	20	1.11	-1	-0.1	4	0.28	100.30	75.56
14	-1.2656	36.80273	69	1699	319	1529133497	1.4	19.17	-0.83	0	-0.9	4	-0.21	109.50	80
15	-1.26516	36.80234	52	1699.6	316	1529133501	1.4	14.44	-4.73	-3	0.6	4	-1.18	102.57	76.68
16	-1.26481	36.80196	33	1700.4	302	1529133507	1.4	9.17	-5.27	-14	0.8	6	-0.88	67.16	86.64
17	-1.26446	36.80164	38	1702.4	339	1529133513	1.4	10.56	1.39	37	2	6	0.23	35.43	55.02
18	-1.264	36.80145	38	1704.5	333	1529133518	1.4	10.56	0	-6	2.1	5	0	42.97	52.8
19	-1.26371	36.80122	26	1710.3	317	1529133523	1.4	7.22	-3.34	-16	5.8	5	-0.67	42.97	52.8
20	-1.26357	36.80109	20	1711.9	323	1529133527	1.4	5.56	-1.66	6	1.6	4	-0.42	25.82	28.88
21	-1.26333	36.80088	29	1721.4	321	1529133533	1.4	8.06	2.5	-2	9.5	6	0.42	18.49	33.36
22	-1.26197	36.79951	65	1724.2	303	1529133547	1.4	18.06	10	-18	2.8	14	0.71	29.80	112.84
23	-1.26123	36.7973	80	1718	281	1529133559	1.4	22.22	4.16	-22	-6.2	12	0.35	93.64	216.72
24	-1.26112	36.79649	82	1713.9	277	1529133563	1.4	22.78	0.56	-4	-4.1	4	0.14	129.01	88.88
25	-1.26102	36.79566	83	1713.8	277	1529133567	1.4	23.06	0.28	0	-0.1	4	0.07	134.12	91.12
26	-1.26084	36.79322	72	1718.9	273	1529133579	1.4	20	-3.06	-4	5.1	12	-0.26	136.71	276.72
27	-1.26077	36.79256	66	1722.5	279	1529133583	1.5	18.33	-1.67	6	3.6	4	-0.42	109.50	80
28	-1.26064	36.79197	56	1724.9	285	1529133587	1.4	15.56	-2.77	6	2.4	4	-0.69	95.84	73.32
29	-1.26049	36.79147	42	1729.3	284	1529133592	1.4	11.67	-3.89	-1	4.4	5	-0.78	74.89	77.8
30	-1.26039	36.79108	43	1728.7	283	1529133596	1.4	11.94	0.27	-1	-0.6	4	0.07	49.42	46.68
31	-1.25943	36.78378	44	1745	278	1529133668	1.1	12.22	0.28	-5	16.3	72	0	51.09	859.68
32	-1.25937	36.7833	50	1745.1	277	1529133672	1.1	13.89	1.67	-1	0.1	4	0.42	52.79	48.88
33	-1.25931	36.78277	54	1745.8	277	1529133676	1.1	15	1.11	0	0.7	4	0.28	63.43	55.56
34	-1.25917	36.78162	61	1750.2	277	1529133684	1.1	16.94	1.94	0	4.4	8	0.24	70.98	120
35	-1.25911	36.78104	56	1752.2	277	1529133688	1.6	15.56	-1.38	0	2	4	-0.35	85.08	67.76
36	-1.259	36.78005	50	1757.5	274	1529133696	1.1	13.89	-1.67	-3	5.3	8	-0.21	74.89	124.48
37	-1.25897	36.77952	56	1761.7	272	1529133700	1.1	15.56	1.67	-2	4.2	4	0.42	63.43	55.56
38	-1.25898	36.77894	59	1764.6	270	1529133704	1.1	16.39	0.83	-2	2.9	4	0.21	74.89	62.24
39	-1.25919	36.77706	66	1769	261	1529133716	1.1	18.33	1.94	-9	4.4	12	0.16	80.93	196.68
40	-1.25955	36.77495	63	1768.1	261	1529133730	0.9	17.5	-0.83	0	-0.9	14	-0.06	95.84	256.62
41	-1.25965	36.77432	66	1768.1	261	1529133734	0.9	18.33	0.83	0	0	4	0.21	89.31	70
42	-1.25979	36.77367	67	1768.8	257	1529133738	0.9	18.61	0.28	-4	0.7	4	0.07	95.84	73.32
43	-1.26019	36.77183	59	1772.3	258	1529133750	0.9	16.39	-2.22	1	3.5	12	-0.19	98.06	223.32
44	-1.26031	36.77126	59	1773.4	258	1529133754	0.9	16.39	0	0	1.1	4	0	80.93	65.56
45	-1.26043	36.77075	54	1774.3	257	1529133758	0.9	15	-1.39	-1	0.9	4	-0.35	80.93	65.56
46	-1.26054	36.77026	51	1776.8	257	1529133762	0.9	14.17	-0.83	0	2.5	4	-0.21	70.98	60
47	-1.26066	36.76972	57	1780.9	259	1529133766	0.9	15.83	1.66	2	4.1	4	0.42	65.28	56.68
48	-1.26077	36.76915	59	1783.5	258	1529133770	0.9	16.39	0.56	-1	2.6	4	0.14	76.88	63.32
49	-1.26089	36.76862	51	1785.3	257	1529133774	0.9	14.17	-2.22	-1	1.8	4	-0.56	80.93	65.56
50	-1.26158	36.76703	55	1786.4	238	1529133788	0.9	15.28	1.11	-19	1.1	14	0.08	65.28	198.38
51	-1.26189	36.76659	52	1786.8	234	1529133792	0.9	14.44	-0.84	-4	0.4	4	-0.21	72.92	61.12
52	-1.26251	36.76573	58	1789.6	237	1529133800	0.9	16.11	1.67	3	2.8	8	0.21	67.16	115.52
53	-1.26279	36.76523	57	1790.3	244	1529133804	0.9	15.83	-0.28	7	0.7	4	-0.07	78.90	64.44
54	-1.263	36.7647	58	1790.9	251	1529133808	0.9	16.11	0.28	7	0.6	4	0.07	76.88	63.32
55	-1.26315	36.76416	56	1791.6	257	1529133812	0.9	15.56	-0.55	6	0.7	4	-0.14	78.90	64.44
56	-1.26326	36.76361	57	1792.9	259	1529133816	0.9	15.83	0.27	2	1.3	4	0.07	74.89	62.24
57	-1.26337	36.76303	59	1794.4	259	1529133820	0.9	16.39	0.56	0	1.5	4	0.14	76.88	63.32
58	-1.26347	36.76247	57	1795.6	260	1529133824	0.9	15.83	-0.56	1	1.2	4	-0.14	80.93	65.56
59	-1.26356	36.76196	51	1797.2	260	1529133828	0.9	14.17	-1.66	0	1.6	4	-0.42	76.88	63.32
60	-1.26365	36.76145	54	1799.7	261	1529133832	0.9	15	0.83	1	2.5	4	0.21	65.28	56.68
61	-1.26372	36.76099	43	1802.1	262	1529133836	0.9	11.94	-3.06	1	2.4	4	-0.77	70.98	60
62	-1.26393	36.75875	51	1805.1	266	1529133854	0.9	14.17	2.23	4	3	18	0.12	51.09	214.92
63	-1.26397	36.75827	46	1806.1	264	1529133858	0.9	12.78	-1.39	-2	1	4	-0.35	65.28	56.68
64	-1.26403	36.75775	34	1809	264	1529133864	0.9	9.44	-3.34	0	2.9	6	-0.56	56.24	76.68
65	-1.2641	36.75722	39	1810.1	263	1529133870	0.9	10.83	1.39	-1	1.1	6	0.23	36.89	56.64
66	-1.26413	36.75687	34	1810.3	264	1529133874	0.9	9.44	-1.39	1	0.2	4	-0.35	44.55	43.32

67	-1.26418	36.75653	35	1810.4	263	1529133878	0.9	9.72	0.28	-1	0.1	4	0.07	36.89	37.76
68	-1.26421	36.756	47	1809.4	269	1529133883	0.9	13.06	3.34	6	-1	5	0.67	38.38	48.6
69	-1.26422	36.75493	45	1809.3	269	1529133894	0.9	12.5	-0.56	0	-0.1	11	-0.05	58.00	143.66
70	-1.26426	36.75307	64	1809.1	270	1529133908	0.9	17.78	5.28	1	-0.2	14	0.38	54.50	175
71	-1.26427	36.75238	70	1809.2	270	1529133912	0.9	19.44	1.66	0	0.1	4	0.42	91.46	71.12
72	-1.26424	36.75168	68	1812.7	272	1529133916	0.9	18.89	-0.55	2	3.5	4	-0.14	104.86	77.76
73	-1.26423	36.75101	70	1816	270	1529133920	0.9	19.44	0.55	-2	3.3	4	0.14	100.30	75.56
74	-1.26424	36.7503	71	1819.1	269	1529133924	0.9	19.72	0.28	-1	3.1	4	0.07	104.86	77.76
75	-1.26424	36.74957	71	1822.7	269	1529133928	0.9	19.72	0	0	3.6	4	0	107.17	78.88
76	-1.26427	36.74886	71	1827	268	1529133932	1	19.72	0	-1	4.3	4	0	107.17	78.88
77	-1.26433	36.7468	54	1831.3	269	1529133944	0.9	15	-4.72	1	4.3	12	-0.39	107.17	236.64

Table 0.14. Driver D2 of the Private Service Vehicle Category

	Lat	Lon	Speed (km/h)	Altitude	Direction (Angle Changes)	GPSTime	GPS Signal Strength	Speed (m/s)	Change in Speed (m/s)	Change in Direction	Change in Altitude	Change in Time (s)	Accl/Decl (m/s^2)	SSD Based on Initial Speed (m)	Actual Distance to Stop (m)
1	-1.32201	36.79163	57	1710	324	1544874925	0.8	15.83							
2	-1.31864	36.78887	64	1712.7	308	1544874956	0.7	17.78	1.95	-16	2.7	31	0.06	76.88	490.73
3	-1.31836	36.78846	67	1714.4	303	1544874959	0.7	18.61	0.83	-5	1.7	3	0.28	91.46	53.34
4	-1.3181	36.78802	69	1716.4	299	1544874962	0.7	19.17	0.56	-4	2	3	0.19	98.06	55.83
5	-1.31838	36.77944	41	1738.3	277	1544875017	0.7	11.39	-7.78	-22	21.9	55	-0.14	102.57	1054.35
6	-1.31827	36.77865	50	1739.8	278	1544875024	0.7	13.89	2.5	1	1.5	7	0.36	47.78	79.73
7	-1.31808	36.7777	48	1741.7	280	1544875032	0.8	13.33	-0.56	2	1.9	8	-0.07	63.43	111.12
8	-1.31796	36.77724	46	1743.2	285	1544875036	0.7	12.78	-0.55	5	1.5	4	-0.14	59.79	53.32
9	-1.31781	36.77668	47	1746.4	286	1544875041	0.8	13.06	0.28	1	3.2	5	0.06	56.24	63.9
10	-1.31767	36.77623	48	1748.3	286	1544875045	0.8	13.33	0.27	0	1.9	4	0.07	58.00	52.24
11	-1.31754	36.77574	51	1749.2	284	1544875049	0.7	14.17	0.84	-2	0.9	4	0.21	59.79	53.32
12	-1.31742	36.77522	55	1749.8	281	1544875053	0.7	15.28	1.11	-3	0.6	4	0.28	65.28	56.68
13	-1.31747	36.77305	67	1755.1	258	1544875067	0.8	18.61	3.33	-23	5.3	14	0.24	72.92	213.92
14	-1.31761	36.77256	68	1757.2	254	1544875070	0.8	18.89	0.28	-4	2.1	3	0.09	98.06	55.83
15	-1.31778	36.77208	67	1760.7	248	1544875073	0.8	18.61	-0.28	-6	3.5	3	-0.09	100.30	56.67
16	-1.32253	36.76132	91	1792.9	240	1544875140	0.8	25.28	6.67	-8	32.2	67	0.1	98.06	1246.87
17	-1.32351	36.76003	93	1793.1	232	1544875147	0.8	25.83	0.55	-8	0.2	7	0.08	158.23	176.96
18	-1.32379	36.75966	92	1793	235	1544875149	0.8	25.56	-0.27	3	-0.1	2	-0.14	163.84	51.66
19	-1.32404	36.75928	91	1792.7	239	1544875151	0.9	25.28	-0.28	4	-0.3	2	-0.14	161.03	51.12
20	-1.32426	36.75887	90	1792.4	244	1544875153	0.8	25	-0.28	5	-0.3	2	-0.14	158.23	50.56
21	-1.32444	36.75846	90	1792.4	248	1544875155	0.8	25	0	4	0	2	0	155.46	50
22	-1.32459	36.75803	90	1792.5	252	1544875157	0.8	25	0	4	0.1	2	0	155.46	50
23	-1.32471	36.75759	91	1793.3	256	1544875159	0.8	25.28	0.28	4	0.8	2	0.14	155.46	50
24	-1.3248	36.75715	91	1794.6	259	1544875161	0.8	25.28	0	3	1.3	2	0	158.23	50.56
25	-1.32495	36.75602	91	1796.1	261	1544875166	0.8	25.28	0	2	1.5	5	0	158.23	126.4
26	-1.32501	36.75557	91	1796.4	261	1544875168	0.8	25.28	0	0	0.3	2	0	158.23	50.56
27	-1.32511	36.75492	87	1796.6	261	1544875171	0.8	24.17	-1.11	0	0.2	3	-0.37	158.23	75.84
28	-1.32549	36.7523	72	1798.5	261	1544875185	0.8	20	-4.17	0	1.9	14	-0.3	147.29	338.38
29	-1.32591	36.74431	84	1810.1	290	1544875228	0.8	23.33	3.33	29	11.6	43	0.08	109.50	860
30	-1.3253	36.74292	88	1813	294	1544875235	0.8	24.44	1.11	4	2.9	7	0.16	139.32	163.31
31	-1.32408	36.74017	96	1813.4	294	1544875248	0.8	26.67	2.23	0	0.4	13	0.17	149.99	317.72
32	-1.32389	36.73972	97	1816.8	294	1544875250	0.8	26.94	0.27	0	3.4	2	0.14	172.43	53.34
33	-1.32369	36.73928	98	1816.9	294	1544875252	0.8	27.22	0.28	0	0.1	2	0.14	175.34	53.88
34	-1.32349	36.73883	97	1817	294	1544875254	0.8	26.94	-0.28	0	0.1	2	-0.14	178.27	54.44
35	-1.3228	36.7376	94	1816.8	304	1544875260	0.8	26.11	-0.83	10	-0.2	6	-0.14	175.34	161.64
36	-1.31227	36.73038	89	1819.3	334	1544875319	0.8	24.72	-1.39	30	2.5	59	-0.02	166.68	1540.49
37	-1.30845	36.72615	76	1825.3	302	1544875352	0.8	21.11	-3.61	-32	6	33	-0.11	152.71	815.76
38	-1.30779	36.72498	77	1827.6	298	1544875359	0.8	21.39	0.28	-4	2.3	7	0.04	119.07	147.77
39	-1.30753	36.72446	77	1829.2	296	1544875362	0.8	21.39	0	-2	1.6	3	0	121.52	64.17
40	-1.30729	36.72394	77	1831	295	1544875365	0.8	21.39	0	-1	1.8	3	0	121.52	64.17
41	-1.30684	36.72288	77	1834	292	1544875371	0.8	21.39	0	-3	3	6	0	121.52	128.34
42	-1.30643	36.72177	80	1836.1	288	1544875377	0.8	22.22	0.83	-4	2.1	6	0.14	121.52	128.34
43	-1.30625	36.72118	83	1836.9	287	1544875380	0.8	23.06	0.84	-1	0.8	3	0.28	129.01	66.66
44	-1.30577	36.71931	89	1839.2	283	1544875389	0.8	24.72	1.66	-4	2.3	9	0.18	136.71	207.54
45	-1.30434	36.71084	39	1862.1	276	1544875439	0.8	10.83	-13.89	-7	22.9	50	-0.28	152.71	1236
46	-1.30426	36.71014	42	1862.3	276	1544875446	0.8	11.67	0.84	0	0.2	7	0.12	44.55	75.81
47	-1.30421	36.70961	43	1865.7	276	1544875451	0.8	11.94	0.27	0	3.4	5	0.05	49.42	58.35
48	-1.30416	36.70906	46	1867.6	275	1544875456	0.8	12.78	0.84	-1	1.9	5	0.17	51.09	59.7
49	-1.3041	36.70849	45	1869.2	275	1544875461	0.8	12.5	-0.28	0	1.6	5	-0.06	56.24	63.9
50	-1.30385	36.70696	46	1871.2	285	1544875475	0.8	12.78	0.28	10	2	14	0.02	54.50	175
51	-1.30355	36.70612	55	1871.7	293	1544875482	0.9	15.28	2.5	8	0.5	7	0.36	56.24	89.46
52	-1.29758	36.69756	90	1870.5	287	1544875535	0.8	25	9.72	-6	-1.2	53	0.18	72.92	809.84
53	-1.29722	36.69608	88	1871.4	282	1544875542	0.8	24.44	-0.56	-5	0.9	7	-0.08	155.46	175
54	-1.29709	36.69543	89	1872.4	281	1544875545	0.8	24.72	0.28	-1	1	3	0.09	149.99	73.32
55	-1.29701	36.69498	91	1872.7	281	1544875547	0.8	25.28	0.56	0	0.3	2	0.28	152.71	49.44
56	-1.29693	36.69453	93	1873.3	280	1544875549	0.8	25.83	0.55	-1	0.6	2	0.27	158.23	50.56
57	-1.29685	36.69406	94	1873.9	281	1544875551	0.8	26.11	0.28	1	0.6	2	0.14	163.84	51.66
58	-1.29677	36.69359	95	1874.5	280	1544875553	0.8	26.39	0.28	-1	0.6	2	0.14	166.68	52.22
59	-1.29669	36.69313	94	1875.3	280	1544875555	0.8	26.11	-0.28	0	0.8	2	-0.14	169.55	52.78
60	-1.29661	36.69266	94	1876.6	281	1544875557	0.8	26.11	0	1	1.3	2	0	166.68	52.22
61	-1.29652	36.6922	93	1878.2	281	1544875559	0.8	25.83	-0.28	0	1.6	2	-0.14	166.68	52.22
62	-1.29643	36.69176	92	1879.7	282	1544875561	0.8	25.56	-0.27	1	1.5	2	-0.14	163.84	51.66
63	-1.29626	36.69112	88	1881.4	286	1544875564	0.8	24.44	-1.12	4	1.7	3	-0.37	161.03	76.68
64	-1.29608	36.69056	77	1882.2	288	1544875567	0.8	21.39	-3.05	2	0.8	3	-1.02	149.99	73.32

65	-1.29439	36.68755	59	1880	308	1544875591	0.8	16.39	-5	20	-2.2	24	-0.21	121.52	513.36
66	-1.29367	36.68675	63	1879.9	314	1544875598	0.8	17.5	1.11	6	-0.1	7	0.16	80.93	114.73
67	-1.29333	36.68641	65	1884	315	1544875601	0.8	18.06	0.56	1	4.1	3	0.19	89.31	52.5
68	-1.29296	36.68607	66	1886.1	318	1544875604	0.8	18.33	0.27	3	2.1	3	0.09	93.64	54.18
69	-1.29257	36.68575	68	1888.1	321	1544875607	0.8	18.89	0.56	3	2	3	0.19	95.84	54.99
70	-1.29215	36.68545	69	1889.5	324	1544875610	0.8	19.17	0.28	3	1.4	3	0.09	100.30	56.67
71	-1.29127	36.68487	70	1892	328	1544875616	0.8	19.44	0.27	4	2.5	6	0.04	102.57	115.02
72	-1.29037	36.68432	70	1896	329	1544875622	0.8	19.44	0	1	4	6	0	104.86	116.64
73	-1.28949	36.68376	67	1900	326	1544875628	0.8	18.61	-0.83	-3	4	6	-0.14	104.86	116.64
74	-1.28461	36.67733	62	1948.2	301	1544875679	0.8	17.22	-1.39	-25	48.2	51	-0.03	98.06	949.11
75	-1.28399	36.67645	64	1953.8	308	1544875686	0.8	17.78	0.56	7	5.6	7	0.08	87.18	120.54
76	-1.28368	36.67608	67	1955.5	311	1544875689	0.8	18.61	0.83	3	1.7	3	0.28	91.46	53.34
77	-1.28333	36.6757	68	1957.4	313	1544875692	0.8	18.89	0.28	2	1.9	3	0.09	98.06	55.83
78	-1.28297	36.67533	69	1959	315	1544875695	0.8	19.17	0.28	2	1.6	3	0.09	100.30	56.67
79	-1.28259	36.67497	72	1960.6	316	1544875698	0.8	20	0.83	1	1.6	3	0.28	102.57	57.51
80	-1.2822	36.67458	75	1962.3	315	1544875701	0.8	20.83	0.83	-1	1.7	3	0.28	109.50	60
81	-1.28178	36.67417	78	1963.7	315	1544875704	0.8	21.67	0.84	0	1.4	3	0.28	116.65	62.49
82	-1.28135	36.67374	80	1965.2	315	1544875707	0.8	22.22	0.55	0	1.5	3	0.18	124.00	65.01
83	-1.28093	36.67333	79	1966.6	315	1544875710	0.8	21.94	-0.28	0	1.4	3	-0.09	129.01	66.66
84	-1.27855	36.67098	80	1977.5	315	1544875727	0.8	22.22	0.28	0	10.9	17	0.02	126.49	372.98
85	-1.27812	36.67056	82	1979.2	316	1544875730	0.8	22.78	0.56	1	1.7	3	0.19	129.01	66.66
86	-1.27768	36.67012	83	1980.5	315	1544875733	0.8	23.06	0.28	-1	1.3	3	0.09	134.12	68.34
87	-1.27559	36.66797	87	1985.5	312	1544875747	0.8	24.17	1.11	-3	5	14	0.08	136.71	322.84
88	-1.2746	36.6668	89	1986.7	309	1544875754	0.8	24.72	0.55	-3	1.2	7	0.08	147.29	169.19
89	-1.27432	36.66645	91	1986.9	309	1544875756	0.8	25.28	0.56	0	0.2	2	0.28	152.71	49.44
90	-1.27404	36.66608	94	1987.1	308	1544875758	0.8	26.11	0.83	-1	0.2	2	0.41	158.23	50.56
91	-1.27375	36.6657	97	1987.2	308	1544875760	0.8	26.94	0.83	0	0.1	2	0.42	166.68	52.22
92	-1.27345	36.66531	97	1986.9	307	1544875762	0.8	26.94	0	-1	-0.3	2	0	175.34	53.88
93	-1.27315	36.66493	96	1986.5	308	1544875764	0.8	26.67	-0.27	1	-0.4	2	-0.14	175.34	53.88
94	-1.27286	36.66455	96	1986.1	308	1544875766	0.8	26.67	0	0	-0.4	2	0	172.43	53.34
95	-1.27257	36.66417	96	1985.7	307	1544875768	0.8	26.67	0	-1	-0.4	2	0	172.43	53.34
96	-1.27228	36.6638	94	1985.4	307	1544875770	0.8	26.11	-0.56	0	-0.3	2	-0.28	172.43	53.34
97	-1.27199	36.66342	94	1985.4	307	1544875772	0.8	26.11	0	0	0	2	0	166.68	52.22
98	-1.27141	36.66266	96	1985.2	307	1544875776	0.8	26.67	0.56	0	-0.2	4	0.14	166.68	104.44
99	-1.26895	36.66049	91	1986.2	330	1544875790	0.8	25.28	-1.39	23	1	14	-0.1	172.43	373.38
100	-1.25885	36.66182	89	2000.5	20	1544875838	0.8	24.72	-0.56	-310	14.3	48	-0.01	158.23	1213.44
101	-1.25842	36.66198	89	2003.9	20	1544875840	0.8	24.72	0	0	3.4	2	0	152.71	49.44
102	-1.2578	36.66221	89	2006.7	21	1544875843	0.8	24.72	0	1	2.8	3	0	152.71	74.16
103	-1.25674	36.66259	90	2008.9	20	1544875848	0.8	25	0.28	-1	2.2	5	0.06	152.71	123.6
104	-1.2557	36.66296	86	2011.3	19	1544875853	0.8	23.89	-1.11	-1	2.4	5	-0.22	155.46	125
105	-1.25454	36.66333	79	2014.6	17	1544875859	0.8	21.94	-1.95	-2	3.3	6	-0.33	144.61	143.34
106	-1.25338	36.66365	83	2015.3	15	1544875865	0.8	23.06	1.12	-2	0.7	6	0.19	126.49	131.64
107	-1.25216	36.66392	83	2014.4	13	1544875871	0.8	23.06	0	-2	-0.9	6	0	136.71	138.36
108	-1.24885	36.66453	81	2020.3	7	1544875888	1	22.5	-0.56	-6	5.9	17	-0.03	136.71	392.02
109	-1.2474	36.66467	83	2022.3	6	1544875895	0.9	23.06	0.56	-1	2	7	0.08	131.55	157.5
110	-1.24467	36.66505	84	2022.8	8	1544875908	0.8	23.33	0.27	2	0.5	13	0.02	136.71	299.78
111	-1.24405	36.66511	81	2029.2	5	1544875911	0.8	22.5	-0.83	-3	6.4	3	-0.28	139.32	69.99
112	-1.24347	36.66516	77	2031.8	7	1544875914	0.8	21.39	-1.11	2	2.6	3	-0.37	131.55	67.5
113	-1.24236	36.66532	77	2035	8	1544875920	0.8	21.39	0	1	3.2	6	0	121.52	128.34
114	-1.24113	36.66552	87	2032.5	10	1544875926	0.8	24.17	2.78	2	-2.5	6	0.46	121.52	128.34
115	-1.23936	36.6658	89	2029.1	11	1544875934	0.8	24.72	0.55	1	-3.4	8	0.07	147.29	193.36
116	-1.23234	36.66849	22	2038.8	336	1544875981	0.8	6.11	-18.61	325	9.7	47	-0.4	152.71	1161.84

Table 0.15. Driver D4 of the Private Service Vehicle Category

	Lat	Lon	Speed (km/h)	Altitude	Direction (Angle Changes)	GPSTime	GPS Signal Strength	Speed (m/s)	Change in Speed (m/s)	Change in Direction	Change in Altitude	Change in Time (s)	Accl/Decl (m/s^2)	SSD Based on Initial Speed (m)	Actual Distance to Stop (m)
1	-1.2356	36.66806	28	2033.9	247	1526649376	0.9	7.78							
2	-1.2359	36.66769	46	2031.8	221	1526649381	0.9	12.78	5	-26	-2.1	5	1	28.45	38.9
3	-1.23633	36.66736	59	2030.2	218	1526649385	0.9	16.39	3.61	-3	-1.6	4	0.9	56.24	51.12
4	-1.23675	36.66705	70	2029.3	214	1526649388	0.9	19.44	3.05	-4	-0.9	3	1.02	80.93	49.17
5	-1.23722	36.66676	75	2029.3	211	1526649391	0.9	20.83	1.39	-3	0	3	0.46	104.86	58.32
6	-1.23773	36.66647	79	2029.8	207	1526649394	0.9	21.94	1.11	-4	0.5	3	0.37	116.65	62.49
7	-1.23829	36.66623	81	2030.4	201	1526649397	0.9	22.5	0.56	-6	0.6	3	0.19	126.49	65.82
8	-1.23889	36.66604	85	2030	196	1526649400	0.9	23.61	1.11	-5	-0.4	3	0.37	131.55	67.5
9	-1.24112	36.66569	95	2028.3	188	1526649410	0.9	26.39	2.78	-8	-1.7	10	0.28	141.95	236.1
10	-1.2416	36.66559	97	2027.8	192	1526649412	0.9	26.94	0.55	4	-0.5	2	0.28	169.55	52.78
11	-1.24209	36.66549	98	2027.8	192	1526649414	0.9	27.22	0.28	0	0	2	0.14	175.34	53.88
12	-1.24685	36.66485	104	2025.8	188	1526649433	0.9	28.89	1.67	-4	-2	19	0.09	178.27	517.18
13	-1.24884	36.66463	98	2023.2	185	1526649441	0.9	27.22	-1.67	-3	-2.6	8	-0.21	196.35	231.12
14	-1.24932	36.66457	98	2024.1	186	1526649443	0.9	27.22	0	1	0.9	2	0	178.27	54.44
15	-1.24981	36.66452	99	2025.2	187	1526649445	0.9	27.5	0.28	1	1.1	2	0.14	178.27	54.44
16	-1.2503	36.66444	100	2025.5	188	1526649447	0.9	27.78	0.28	1	0.3	2	0.14	181.23	55
17	-1.25325	36.66377	99	2016.8	194	1526649459	0.9	27.5	-0.28	6	-8.7	12	-0.02	184.21	333.36
18	-1.25514	36.66324	98	2013.1	197	1526649467	0.9	27.22	-0.28	3	-3.7	8	-0.04	181.23	220
19	-1.25706	36.66259	104	2009.2	200	1526649475	0.9	28.89	1.67	3	-3.9	8	0.21	178.27	217.76
20	-1.26331	36.66028	86	1993.7	199	1526649502	0.9	23.89	-5	-1	-15.5	27	-0.19	196.35	780.03
21	-1.26394	36.66008	87	1993.5	196	1526649505	0.9	24.17	0.28	-3	-0.2	3	0.09	144.61	71.67
22	-1.26457	36.65994	86	1993	192	1526649508	0.9	23.89	-0.28	-4	-0.5	3	-0.09	147.29	72.51
23	-1.2652	36.65986	84	1992.5	186	1526649511	0.9	23.33	-0.56	-6	-0.5	3	-0.19	144.61	71.67
24	-1.26584	36.65983	86	1993.2	181	1526649514	0.9	23.89	0.56	-5	0.7	3	0.19	139.32	69.99
25	-1.27007	36.66139	95	1989.6	143	1526649534	0.9	26.39	2.5	-38	-3.6	20	0.13	144.61	477.8
26	-1.27044	36.66171	98	1988.5	139	1526649536	0.9	27.22	0.83	-4	-1.1	2	0.41	169.55	52.78
27	-1.27533	36.66777	99	1988.4	130	1526649567	0.9	27.5	0.28	-9	-0.1	31	0.01	178.27	843.82
28	-1.27776	36.67033	100	1978	136	1526649581	0.9	27.78	0.28	6	-10.4	14	0.02	181.23	385
29	-1.27811	36.67067	100	1976.9	135	1526649583	0.9	27.78	0	-1	-1.1	2	0	184.21	55.56
30	-1.27847	36.67103	101	1976.1	135	1526649585	0.9	28.06	0.28	0	-0.8	2	0.14	184.21	55.56
31	-1.28029	36.67282	105	1969.9	135	1526649595	0.9	29.17	1.11	0	-6.2	10	0.11	187.21	280.6
32	-1.28368	36.6762	93	1958.1	132	1526649614	0.9	25.83	-3.34	-3	-11.8	19	-0.18	199.44	554.23
33	-1.2847	36.67751	73	1949.2	123	1526649622	0.9	20.28	-5.55	-9	-8.9	8	-0.69	163.84	206.64
34	-1.28493	36.6779	60	1946.4	120	1526649625	0.9	16.67	-3.61	-3	-2.8	3	-1.2	111.86	60.84
35	-1.28521	36.67845	68	1942.9	117	1526649629	0.9	18.89	2.22	-3	-3.5	4	0.56	82.99	66.68
36	-1.28545	36.67894	75	1940.7	117	1526649632	0.9	20.83	1.94	0	-2.2	3	0.65	100.30	56.67
37	-1.28571	36.67947	80	1938.5	117	1526649635	0.9	22.22	1.39	0	-2.2	3	0.46	116.65	62.49
38	-1.28599	36.68001	82	1935.7	118	1526649638	0.9	22.78	0.56	1	-2.8	3	0.19	129.01	66.66
39	-1.28694	36.68144	72	1925.8	127	1526649647	0.9	20	-2.78	9	-9.9	9	-0.31	134.12	205.02
40	-1.2873	36.68189	79	1923.2	129	1526649650	0.9	21.94	1.94	2	-2.6	3	0.65	109.50	60
41	-1.28771	36.68237	86	1920.1	131	1526649653	0.9	23.89	1.95	2	-3.1	3	0.65	126.49	65.82
42	-1.29064	36.68463	87	1905.8	148	1526649672	0.9	24.17	0.28	17	-14.3	19	0.01	144.61	453.91
43	-1.29103	36.68487	92	1904.7	148	1526649674	0.9	25.56	1.39	0	-1.1	2	0.69	147.29	48.34
44	-1.29186	36.68536	97	1900.4	148	1526649678	0.9	26.94	1.38	0	-4.3	4	0.35	161.03	102.24
45	-1.29574	36.68986	102	1884	115	1526649702	0.9	28.33	1.39	-33	-16.4	24	0.06	175.34	646.56
46	-1.29635	36.69171	97	1882.5	105	1526649710	0.9	26.94	-1.39	-10	-1.5	8	-0.17	190.23	226.64
47	-1.29646	36.69219	99	1882.2	102	1526649712	0.9	27.5	0.56	-3	-0.3	2	0.28	175.34	53.88
48	-1.29654	36.69268	100	1881.7	100	1526649714	0.9	27.78	0.28	-2	-0.5	2	0.14	181.23	55
49	-1.29663	36.69318	101	1880.7	101	1526649716	0.9	28.06	0.28	1	-1	2	0.14	184.21	55.56
50	-1.29761	36.69792	104	1876.4	106	1526649735	0.9	28.89	0.83	5	-4.3	19	0.04	187.21	533.14
51	-1.29837	36.69976	98	1874.4	116	1526649743	0.9	27.22	-1.67	10	-2	8	-0.21	196.35	231.12
52	-1.29859	36.70019	96	1874.4	118	1526649745	0.9	26.67	-0.55	2	0	2	-0.27	178.27	54.44
53	-1.29883	36.7006	94	1874.4	121	1526649747	0.9	26.11	-0.56	3	0	2	-0.28	172.43	53.34
54	-1.29908	36.701	95	1874.2	123	1526649749	0.9	26.39	0.28	2	-0.2	2	0.14	166.68	52.22
55	-1.29935	36.70139	96	1873.9	126	1526649751	0.9	26.67	0.28	3	-0.3	2	0.14	169.55	52.78
56	-1.30275	36.70506	102	1869.2	132	1526649771	0.9	28.33	1.66	6	-4.7	20	0.08	172.43	533.4
57	-1.30335	36.70588	102	1869.8	121	1526649775	0.9	28.33	0	-11	0.6	4	0	190.23	113.32
58	-1.30428	36.71064	105	1864.5	97	1526649794	0.9	29.17	0.84	-24	-5.3	19	0.04	190.23	538.27
59	-1.30454	36.71271	104	1857.4	98	1526649802	0.9	28.89	-0.28	1	-7.1	8	-0.04	199.44	233.36
60	-1.30461	36.71321	101	1857	98	1526649804	0.9	28.06	-0.83	0	-0.4	2	-0.42	196.35	57.78
61	-1.30467	36.71372	102	1856.5	97	1526649806	0.9	28.33	0.27	-1	-0.5	2	0.14	187.21	56.12
62	-1.30482	36.71473	103	1855.2	100	1526649810	0.9	28.61	0.28	3	-1.3	4	0.07	190.23	113.32
63	-1.30491	36.71524	106	1854.2	100	1526649812	0.9	29.44	0.83	0	-1	2	0.42	193.28	57.22
64	-1.305	36.71577	106	1853.2	101	1526649814	0.9	29.44	0	1	-1	2	0	202.55	58.88

65	-1.3051	36.71629	104	1852.1	101	1526649816	0.9	28.89	-0.55	0	-1.1	2	-0.28	202.55	58.88
66	-1.3053	36.7173	102	1849.6	102	1526649820	0.9	28.33	-0.56	1	-2.5	4	-0.14	196.35	115.56
67	-1.3054	36.7178	102	1848.9	102	1526649822	0.9	28.33	0	0	-0.7	2	0	190.23	56.66
68	-1.3055	36.71831	104	1848.6	101	1526649824	0.9	28.89	0.56	-1	-0.3	2	0.28	190.23	56.66
69	-1.30561	36.71883	106	1848.2	102	1526649826	0.9	29.44	0.55	1	-0.4	2	0.28	196.35	57.78
70	-1.30573	36.71937	111	1847.8	103	1526649828	0.9	30.83	1.39	1	-0.4	2	0.69	202.55	58.88
71	-1.30586	36.71992	115	1847.3	103	1526649830	0.9	31.94	1.11	0	-0.5	2	0.56	218.47	61.66
72	-1.30615	36.72108	122	1847.3	105	1526649834	0.9	33.89	1.95	2	0	4	0.49	231.62	127.76
73	-1.30632	36.72168	124	1847.1	107	1526649836	0.9	34.44	0.55	2	-0.2	2	0.27	255.52	67.78
74	-1.30857	36.72656	104	1827.9	121	1526649855	0.9	28.89	-5.55	14	-19.2	19	-0.29	262.55	654.36
75	-1.30958	36.728	77	1824.2	127	1526649863	0.9	21.39	-7.5	6	-3.7	8	-0.94	196.35	231.12
76	-1.30986	36.72839	61	1823.9	124	1526649866	0.9	16.94	-4.45	-3	-0.3	3	-1.48	121.52	64.17
77	-1.30995	36.72884	49	1823.3	90	1526649870	0.9	13.61	-3.33	-34	-0.6	4	-0.83	85.08	67.76

APPENDIX F: SAMPLE AGENT TRAINING, TESTING AND EVALUATION DATA

Table 0.16. Sample Agent Training Data

Data Point	Driver	Lat	Lon	Spd (km/h)	Alt	Dir	Dir (^{0})	Time	GPSTime	GPS Signal Strength	Spd (m/s)	ΔSpd (m/s^2)	ΔDir (^{0})	ΔAlt (m)	ΔTm (s)	Accel/ Decel (m/s^2)
1	Dr	-1.39933	36.79036	0	1703.3	SE	137	1/19/2019 1:53	1547895232	0.8	0					
2	Dr	-1.39934	36.79033	4	1708.7	NW	345	1/19/2019 2:09	1547896145	0.8	1.11	1.11	208	5.4	913	0
3	Dr	-1.39933	36.79033	3	1708.7	SW	258	1/19/2019 2:09	1547896150	0.8	0.83	-0.28	-87	0	5	-0.06
4	Dr	-1.39946	36.78988	17	1694.1	SW	238	1/19/2019 2:09	1547896165	0.8	4.72	3.89	-20	-14.6	15	0.26
5	Dr	-1.39971	36.78944	13	1692.1	SW	238	1/19/2019 2:09	1547896177	0.8	3.61	-1.11	0	-2	12	-0.09
6	Dr	-1.39991	36.78923	14	1686	SW	206	1/19/2019 2:09	1547896185	0.9	3.89	0.28	-32	-6.1	8	0.04
7	Dr	-1.40011	36.78917	12	1689.3	SW	214	1/19/2019 2:09	1547896191	0.8	3.33	-0.56	8	3.3	6	-0.09
8	Dr	-1.40016	36.78909	11	1690.3	SW	254	1/19/2019 2:09	1547896194	0.8	3.06	-0.27	40	1	3	-0.09
9	Dr	-1.4001	36.78895	3	1718.3	NW	331	1/19/2019 2:10	1547896240	0.8	0.83	-2.23	77	28	46	-0.05
10	Dr	-1.39995	36.7888	12	1714.7	SW	269	1/19/2019 2:10	1547896249	0.8	3.33	2.5	-62	-3.6	9	0.28
11	Dr	-1.40012	36.78824	6	1712.6	SW	248	1/19/2019 2:11	1547896266	0.8	1.67	-1.66	-21	-2.1	17	-0.1
12	Dr	-1.4003	36.78773	18	1708.6	SW	250	1/19/2019 2:11	1547896281	0.8	5	3.33	2	-4	15	0.22
13	Dr	-1.40046	36.78726	28	1709.8	SW	250	1/19/2019 2:11	1547896289	0.8	7.78	2.78	0	1.2	8	0.35
14	Dr	-1.40065	36.78678	30	1708.5	SW	249	1/19/2019 2:11	1547896296	0.8	8.33	0.55	-1	-1.3	7	0.08
15	Dr	-1.40084	36.78634	33	1708	SW	245	1/19/2019 2:11	1547896302	0.8	9.17	0.84	-4	-0.5	6	0.14
16	Dr	-1.40107	36.78588	34	1709.3	SW	243	1/19/2019 2:11	1547896308	0.8	9.44	0.27	-2	1.3	6	0.04
17	Dr	-1.4013	36.78539	36	1708.7	SW	245	1/19/2019 2:11	1547896314	0.8	10	0.56	2	-0.6	6	0.09
18	Dr	-1.40167	36.78425	32	1711.1	SW	265	1/19/2019 2:12	1547896328	0.8	8.89	-1.11	20	2.4	14	-0.08
19	Dr	-1.40154	36.78377	36	1712.7	NW	303	1/19/2019 2:12	1547896334	0.8	10	1.11	38	1.6	6	0.19
20	Dr	-1.40121	36.7834	39	1714.8	NW	313	1/19/2019 2:12	1547896339	0.8	10.83	0.83	10	2.1	5	0.17
21	Dr	-1.40093	36.78311	40	1716.3	NW	314	1/19/2019 2:12	1547896343	0.8	11.11	0.28	1	1.5	4	0.07
22	Dr	-1.40079	36.78296	41	1716.5	NW	312	1/19/2019 2:12	1547896345	0.8	11.39	0.28	-2	0.2	2	0.14
23	Dr	-1.40043	36.78258	43	1716.5	NW	314	1/19/2019 2:12	1547896350	0.8	11.94	0.55	2	0	5	0.11
24	Dr	-1.40005	36.78221	43	1716.3	NW	314	1/19/2019 2:12	1547896355	0.8	11.94	0	0	-0.2	5	0
25	Dr	-1.39967	36.78183	42	1716.7	NW	314	1/19/2019 2:12	1547896360	0.8	11.67	-0.27	0	0.4	5	-0.05
26	Dr	-1.39929	36.78144	44	1719.4	NW	313	1/19/2019 2:12	1547896365	0.8	12.22	0.55	-1	2.7	5	0.11
27	Dr	-1.39892	36.78104	43	1720.9	NW	312	1/19/2019 2:12	1547896370	0.8	11.94	-0.28	-1	1.5	5	-0.06
28	Dr	-1.39771	36.77977	46	1722.9	NW	315	1/19/2019 2:13	1547896386	0.8	12.78	0.84	3	2	16	0.05
29	Dr	-1.39738	36.77944	47	1722.3	NW	316	1/19/2019 2:13	1547896390	0.8	13.06	0.28	1	-0.6	4	0.07
30	Dr	-1.3967	36.77875	36	1723.9	NW	313	1/19/2019 2:13	1547896399	0.8	10	-3.06	-3	1.6	9	-0.34
31	Dr	-1.39651	36.77857	10	1724.2	NE	5	1/19/2019 2:13	1547896408	0.9	2.78	-7.22	-308	0.3	9	-0.8
32	Dr	-1.39634	36.77874	24	1722.5	NE	51	1/19/2019 2:13	1547896413	0.8	6.67	3.89	46	-1.7	5	0.78
33	Dr	-1.39603	36.77916	38	1722.4	NE	52	1/19/2019 2:13	1547896419	0.8	10.56	3.89	1	-0.1	6	0.65
34	Dr	-1.39571	36.77959	44	1722.5	NE	53	1/19/2019 2:13	1547896424	0.8	12.22	1.66	1	0.1	5	0.33
35	Dr	-1.3954	36.77993	47	1722.3	NE	43	1/19/2019 2:13	1547896428	0.8	13.06	0.84	-10	-0.2	4	0.21
36	Dr	-1.39499	36.78019	47	1720.6	NE	28	1/19/2019 2:13	1547896432	0.8	13.06	0	-15	-1.7	4	0
37	Dr	-1.39477	36.78029	47	1719.7	NE	24	1/19/2019 2:13	1547896434	0.8	13.06	0	-4	-0.9	2	0
38	Dr	-1.39332	36.78114	44	1710.1	NE	44	1/19/2019 2:14	1547896448	0.8	12.22	-0.84	20	-9.6	14	-0.06
39	Dr	-1.39296	36.78156	44	1712.2	NE	45	1/19/2019 2:14	1547896453	0.8	12.22	0	1	2.1	5	0
40	Dr	-1.39255	36.78191	44	1713.8	NE	37	1/19/2019 2:14	1547896458	0.9	12.22	0	-8	1.6	5	0
41	Dr	-1.39211	36.78217	36	1712.7	NE	27	1/19/2019 2:14	1547896463	0.9	10	-2.22	-10	-1.1	5	-0.44
42	Dr	-1.39193	36.7822	14	1708.8	NW	351	1/19/2019 2:14	1547896467	0.8	3.89	-6.11	324	-3.9	4	-1.53
43	Dr	-1.3919	36.78215	12	1707.4	NW	286	1/19/2019 2:14	1547896469	0.8	3.33	-0.56	-65	-1.4	2	-0.28
44	Dr	-1.39199	36.78191	24	1699.9	SW	249	1/19/2019 2:14	1547896474	0.9	6.67	3.34	-37	-7.5	5	0.67
45	Dr	-1.39214	36.78147	30	1689.8	SW	254	1/19/2019 2:14	1547896480	0.9	8.33	1.66	5	-10.1	6	0.28
46	Dr	-1.39229	36.78096	19	1686	SW	255	1/19/2019 2:14	1547896492	0.9	5.28	-3.05	1	-3.8	12	-0.25
47	Dr	-1.39257	36.78021	27	1682.1	SW	246	1/19/2019 2:15	1547896507	1	7.5	2.22	-9	-3.9	15	0.15
48	Dr	-1.39278	36.77971	32	1677.1	SW	249	1/19/2019 2:15	1547896514	0.9	8.89	1.39	3	-5	7	0.2
49	Dr	-1.39296	36.77923	11	1674.7	SW	251	1/19/2019 2:15	1547896528	0.9	3.06	-5.83	2	-2.4	14	-0.42
50	Dr	-1.39307	36.77873	20	1685.8	SW	260	1/19/2019 2:15	1547896542	0.9	5.56	2.5	9	11.1	14	0.18
51	Dr	-1.39305	36.77817	23	1690.7	NW	280	1/19/2019 2:15	1547896553	1	6.39	0.83	20	4.9	11	0.08
52	Dr	-1.39252	36.77715	37	1700	NW	303	1/19/2019 2:16	1547896567	0.9	10.28	3.89	23	9.3	14	0.28
53	Dr	-1.39224	36.77673	39	1703.5	NW	302	1/19/2019 2:16	1547896572	0.9	10.83	0.55	-1	3.5	5	0.11
54	Dr	-1.39198	36.77633	39	1706.3	NW	302	1/19/2019 2:16	1547896577	0.9	10.83	0	0	2.8	5	0
55	Dr	-1.39172	36.77593	39	1709.6	NW	302	1/19/2019 2:16	1547896582	0.9	10.83	0	0	3.3	5	0
56	Dr	-1.39148	36.77552	36	1713	NW	298	1/19/2019 2:16	1547896587	0.9	10	-0.83	-4	3.4	5	-0.17
57	Dr	-1.39112	36.7746	34	1721.5	NW	283	1/19/2019 2:16	1547896599	0.9	9.44	-0.56	-15	8.5	12	-0.05
58	Dr	-1.39107	36.77413	38	1722.9	NW	275	1/19/2019 2:16	1547896604	0.9	10.56	1.12	-8	1.4	5	0.22
59	Dr	-1.39105	36.77367	35	1723.8	NW	275	1/19/2019 2:16	1547896609	0.9	9.72	-0.84	0	0.9	5	-0.17
60	Dr	-1.39102	36.77265	31	1721.8	NW	272	1/19/2019 2:17	1547896627	0.9	8.61	-1.11	-3	-2	18	-0.06
61	Dr	-1.39097	36.77214	35	1724.2	NW	274	1/19/2019 2:17	1547896633	0.9	9.72	1.11	2	2.4	6	0.19
62	Dr	-1.39093	36.77168	39	1726.3	NW	275	1/19/2019 2:17	1547896638	0.9	10.83	1.11	1	2.1	5	0.22
63	Dr	-1.39089	36.77119	39	1727	NW	276	1/19/2019 2:17	1547896643	0.9	10.83	0	1	0.7	5	0
64	Dr	-1.39082	36.77072	38	1729	NW	277	1/19/2019 2:17	1547896648	0.9	10.56	-0.27	1	2	5	-0.05
65	Dr	-1.39077	36.77025	19	1732.3	NW	278	1/19/2019 2:17	1547896655	0.9	5.28	-5.28	1	3.3	7	-0.75
66	Dr	-1.39075	36.76977	26	1732.3	SW	269	1/19/2019 2:17	1547896663	0.9	7.22	1.94	-9	0	8	0.24
67	Dr	-1.39075	36.76925	26	1725.8	SW	264	1/19/2019 2:17	1547896671	0.9	7.22	0	-5	-6.5	8	0
68	Dr	-1.39081	36.76811	30	1718.4	SW	268	1/19/2019 2:18	1547896687	0.9	8.33	1.11	4	-7.4	16	0.07
69	Dr	-1.39079	36.76756	32	1715.5	NW	278	1/19/2019 2:18	1547896694	0.9	8.89	0.56	10	-2.9	7	0.08
70	Dr	-1.39062	36.76707	12	1715.4	NW	291	1/19/2019 2:18	1547896706	0.9	3.33	-5.56	13	-0.1	12	-0.46
71	Dr	-1.39053	36.76697	3	1714.8	NW	334	1/19/2019 2:18	1547896722	0.9	0.83	-2.5	43	-0.6	16	-0.16
72	Dr	-1.39048	36.76696	10	1713.7	NE	11	1/19/2019 2:18	1547896726	0.9	2.78	1.95	-323	-1.1	4	0.49
73	Dr	-1.39013	36.7672	33	1711.6	NE	39	1/19/2019 2:18	1547896733	0.9	9.17	6.39	28	-2.1	7	0.91
74	Dr	-1.3891	36.76838	48	1707.3	NE	65	1/19/2019 2:19	1547896747	0.9	13.33	4.16	26	-4.3	14	0.3

75	Dr	-1.38892	36.76882	46	1706.9	NE	68	1/19/2019 2:19	1547896751	0.9	12.78	-0.55	3	-0.4	4	-0.14
76	Dr	-1.38869	36.76928	39	1706.9	NE	56	1/19/2019 2:19	1547896756	0.8	10.83	-1.95	-12	0	5	-0.39
77	Dr	-1.38833	36.76967	33	1707.4	NE	46	1/19/2019 2:19	1547896762	0.8	9.17	-1.66	-10	0.5	6	-0.28
78	Dr	-1.38796	36.77002	29	1710.5	NE	45	1/19/2019 2:19	1547896769	0.8	8.06	-1.11	-1	3.1	7	-0.16
79	Dr	-1.38757	36.77041	33	1713.8	NE	45	1/19/2019 2:19	1547896776	0.8	9.17	1.11	0	3.3	7	0.16
80	Dr	-1.38716	36.77076	29	1715.6	NE	40	1/19/2019 2:19	1547896783	0.8	8.06	-1.11	-5	1.8	7	-0.16
81	Dr	-1.38675	36.77102	26	1721.7	NE	27	1/19/2019 2:19	1547896791	0.8	7.22	-0.84	-13	6.1	8	-0.11
82	Dr	-1.38662	36.77107	26	1722.3	NE	21	1/19/2019 2:19	1547896793	0.8	7.22	0	-6	0.6	2	0
83	Dr	-1.38341	36.77075	37	1725	NW	352	1/19/2019 2:20	1547896828	0.8	10.28	3.06	331	2.7	35	0.09
84	Dr	-1.38293	36.77068	24	1718.7	NW	352	1/19/2019 2:20	1547896838	0.8	6.67	-3.61	0	-6.3	10	-0.36
85	Dr	-1.38246	36.77062	28	1717.6	NW	353	1/19/2019 2:20	1547896846	0.8	7.78	1.11	1	-1.1	8	0.14
86	Dr	-1.38199	36.77055	34	1718.7	NW	352	1/19/2019 2:20	1547896852	0.8	9.44	1.66	-1	1.1	6	0.28
87	Dr	-1.38083	36.77038	19	1719.4	NW	353	1/19/2019 2:21	1547896867	0.8	5.28	-4.16	1	0.7	15	-0.28
88	Dr	-1.38036	36.77031	28	1723.4	NW	351	1/19/2019 2:21	1547896875	0.9	7.78	2.5	-2	4	8	0.31
89	Dr	-1.37987	36.77025	36	1725.4	NW	352	1/19/2019 2:21	1547896881	0.9	10	2.22	1	2	6	0.37
90	Dr	-1.37938	36.77019	41	1727	NW	352	1/19/2019 2:21	1547896886	0.9	11.39	1.39	0	1.6	5	0.28
91	Dr	-1.37887	36.77011	41	1729.2	NW	352	1/19/2019 2:21	1547896891	0.9	11.39	0	0	2.2	5	0
92	Dr	-1.37839	36.77004	38	1732.7	NW	352	1/19/2019 2:21	1547896896	0.9	10.56	-0.83	0	3.5	5	-0.17
93	Dr	-1.37785	36.76997	36	1739	NW	351	1/19/2019 2:21	1547896902	0.9	10	-0.56	-1	6.3	6	-0.09
94	Dr	-1.37735	36.76989	25	1745.8	NW	352	1/19/2019 2:21	1547896909	0.9	6.94	-3.06	1	6.8	7	-0.44
95	Dr	-1.37636	36.76977	33	1750.6	NW	349	1/19/2019 2:22	1547896927	0.9	9.17	2.23	-3	4.8	18	0.12
96	Dr	-1.37592	36.76969	36	1760.6	NW	351	1/19/2019 2:22	1547896932	0.9	10	0.83	2	10	5	0.17
97	Dr	-1.37543	36.76962	41	1764.6	NW	351	1/19/2019 2:22	1547896937	0.9	11.39	1.39	0	4	5	0.28
98	Dr	-1.37491	36.76955	42	1767.2	NW	352	1/19/2019 2:22	1547896942	0.9	11.67	0.28	1	2.6	5	0.06
99	Dr	-1.37436	36.76946	45	1766.8	NW	347	1/19/2019 2:22	1547896947	0.9	12.5	0.83	-5	-0.4	5	0.17
100	Dr	-1.37391	36.76934	47	1765.2	NW	343	1/19/2019 2:22	1547896951	0.9	13.06	0.56	-4	-1.6	4	0.14
101	Dr	-1.37337	36.76916	44	1763.1	NW	340	1/19/2019 2:22	1547896956	0.9	12.22	-0.84	-3	-2.1	5	-0.17
102	Dr	-1.37287	36.76895	44	1764.9	NW	336	1/19/2019 2:22	1547896961	0.9	12.22	0	-4	1.8	5	0
103	Dr	-1.37238	36.76871	43	1771.3	NW	334	1/19/2019 2:22	1547896966	0.9	11.94	-0.28	-2	6.4	5	-0.06
104	Dr	-1.3719	36.76847	42	1777.4	NW	333	1/19/2019 2:22	1547896971	0.9	11.67	-0.27	-1	6.1	5	-0.05
105	Dr	-1.37143	36.76823	42	1781.8	NW	333	1/19/2019 2:22	1547896976	0.9	11.67	0	0	4.4	5	0
106	Dr	-1.37009	36.76757	43	1788	NW	336	1/19/2019 2:23	1547896990	0.9	11.94	0.27	3	6.2	14	0.02
107	Dr	-1.36958	36.76743	42	1788.2	NW	353	1/19/2019 2:23	1547896995	0.9	11.67	-0.27	17	0.2	5	-0.05
108	Dr	-1.36904	36.76746	43	1784.2	NE	8	1/19/2019 2:23	1547897000	0.9	11.94	0.27	-345	-4	5	0.05
109	Dr	-1.36849	36.76757	45	1782.1	NE	12	1/19/2019 2:23	1547897005	0.9	12.5	0.56	4	-2.1	5	0.11
110	Dr	-1.36795	36.76765	42	1782	NE	2	1/19/2019 2:23	1547897010	0.9	11.67	-0.83	-10	-0.1	5	-0.17
111	Dr	-1.36742	36.76758	43	1781.3	NW	346	1/19/2019 2:23	1547897015	0.9	11.94	0.27	344	-0.7	5	0.05
112	Dr	-1.36647	36.76711	40	1783.3	NW	331	1/19/2019 2:23	1547897025	0.9	11.11	-0.83	-15	2	10	-0.08
113	Dr	-1.36604	36.76686	25	1782.5	NW	331	1/19/2019 2:23	1547897033	0.9	6.94	-4.17	0	-0.8	8	-0.52
114	Dr	-1.36585	36.76675	32	1781.7	NW	332	1/19/2019 2:23	1547897036	0.9	8.89	1.95	1	-0.8	3	0.65
115	Dr	-1.36469	36.7661	36	1774.7	NW	332	1/19/2019 2:24	1547897050	0.9	10	1.11	0	-7	14	0.08
116	Dr	-1.36427	36.76586	17	1777.7	NW	328	1/19/2019 2:24	1547897058	0.9	4.72	-5.28	-4	3	8	-0.66
117	Dr	-1.36384	36.76554	30	1780	NW	318	1/19/2019 2:24	1547897067	0.9	8.33	3.61	-10	2.3	9	0.4
118	Dr	-1.36348	36.76522	34	1783.9	NW	318	1/19/2019 2:24	1547897073	0.9	9.44	1.11	0	3.9	6	0.19
119	Dr	-1.36307	36.76484	40	1788.2	NW	318	1/19/2019 2:24	1547897079	0.9	11.11	1.67	0	4.3	6	0.28
120	Dr	-1.3627	36.76451	39	1791.5	NW	318	1/19/2019 2:24	1547897084	0.9	10.83	-0.28	0	3.3	5	-0.06
121	Dr	-1.36232	36.76416	41	1793.1	NW	318	1/19/2019 2:24	1547897089	0.9	11.39	0.56	0	1.6	5	0.11
122	Dr	-1.36194	36.76379	43	1793.8	NW	317	1/19/2019 2:24	1547897094	0.9	11.94	0.55	-1	0.7	5	0.11
123	Dr	-1.36086	36.76288	40	1795.6	NW	328	1/19/2019 2:25	1547897108	0.9	11.11	-0.83	11	1.8	14	-0.06
124	Dr	-1.36037	36.7627	43	1796.1	NW	346	1/19/2019 2:25	1547897113	0.9	11.94	0.83	18	0.5	5	0.17
125	Dr	-1.35983	36.76264	43	1793.3	NW	356	1/19/2019 2:25	1547897118	0.9	11.94	0	10	-2.8	5	0
126	Dr	-1.3593	36.76261	42	1791	NW	357	1/19/2019 2:25	1547897123	0.9	11.67	-0.27	1	-2.3	5	-0.05
127	Dr	-1.35877	36.76258	42	1789.6	NW	357	1/19/2019 2:25	1547897128	0.9	11.67	0	0	-1.4	5	0
128	Dr	-1.35825	36.76255	41	1788.2	NW	356	1/19/2019 2:25	1547897133	0.9	11.39	-0.28	-1	-1.4	5	-0.06
129	Dr	-1.35773	36.76248	41	1788.4	NW	349	1/19/2019 2:25	1547897138	0.9	11.39	0	-7	0.2	5	0
130	Dr	-1.35723	36.76236	41	1787.5	NW	347	1/19/2019 2:25	1547897143	0.9	11.39	0	-2	-0.9	5	0
131	Dr	-1.35677	36.76226	33	1786.9	NW	346	1/19/2019 2:25	1547897148	0.9	9.17	-2.22	-1	-0.6	5	-0.44
132	Dr	-1.35557	36.76196	17	1788.2	NW	346	1/19/2019 2:26	1547897168	0.9	4.72	-4.45	0	1.3	20	-0.22
133	Dr	-1.35501	36.76186	35	1787.8	NW	354	1/19/2019 2:26	1547897177	0.9	9.72	5	8	-0.4	9	0.56
134	Dr	-1.35482	36.76186	39	1787.5	NE	1	1/19/2019 2:26	1547897179	0.9	10.83	1.11	-353	-0.3	2	0.56
135	Dr	-1.3545	36.76191	45	1785.1	NE	14	1/19/2019 2:26	1547897182	0.9	12.5	1.67	13	-2.4	3	0.56
136	Dr	-1.354	36.76211	56	1781.7	NE	24	1/19/2019 2:26	1547897186	0.9	15.56	3.06	10	-3.4	4	0.77
137	Dr	-1.35346	36.76237	60	1779.3	NE	25	1/19/2019 2:26	1547897190	1	16.67	1.11	1	-2.4	4	0.28
138	Dr	-1.35306	36.76257	59	1779.4	NE	26	1/19/2019 2:26	1547897193	0.9	16.39	-0.28	1	0.1	3	-0.09
139	Dr	-1.35262	36.76278	45	1784.3	NE	22	1/19/2019 2:26	1547897197	0.9	12.5	-3.89	-4	4.9	4	-0.97
140	Dr	-1.35215	36.76289	36	1790.9	NE	12	1/19/2019 2:26	1547897202	0.9	10	-2.5	-10	6.6	5	-0.5
141	Dr	-1.35165	36.76296	34	1795.5	NE	11	1/19/2019 2:26	1547897208	0.9	9.44	-0.56	-1	4.6	6	-0.09
142	Dr	-1.35117	36.7631	34	1798.8	NE	21	1/19/2019 2:26	1547897214	0.9	9.44	0	10	3.3	6	0
143	Dr	-1.34988	36.76399	55	1794.5	NE	35	1/19/2019 2:27	1547897228	0.9	15.28	5.84	14	-4.3	14	0.42
144	Dr	-1.34938	36.76433	61	1789.8	NE	35	1/19/2019 2:27	1547897232	0.9	16.94	1.66	0	-4.7	4	0.42
145	Dr	-1.34898	36.76457	59	1789.1	NE	27	1/19/2019 2:27	1547897235	0.9	16.39	-0.55	-8	-0.7	3	-0.18
146	Dr	-1.34848	36.76475	47	1790.8	NE	17	1/19/2019 2:27	1547897239	0.9	13.06	-3.33	-10	1.7	4	-0.83
147	Dr	-1.34797	36.76489	41	1794.7	NE	17	1/19/2019 2:27	1547897244	0.9	11.39	-1.67	0	3.9	5	-0.33
148	Dr	-1.34748	36.76506	43	1798.3	NE	20	1/19/2019 2:27	1547897249	0.9	11.94	0.55	3	3.6	5	0.11
149	Dr	-1.34698	36.76524	43	1799.6	NE	21	1/19/2019 2:27	1547897254	0.9	11.94	0	1	1.3	5	0
150	Dr	-1.34651	36.7654	15	1800.1	NE	20	1/19/2019 2:27	1547897263	0.9	4.17	-7.77	-1	0.5	9	-0.86
151	Dr	-1.346	36.76558	24	1799.5	NE	20	1/19/2019 2:27	1547897273	0.9	6.67	2.5	0	-0.6	10	0.25
152	Dr	-1.34522	36.76583	29	1798.3	NE	15	1/19/2019 2:28	1547897288	0.9	8.06	1.39	-5	-1.2	15	0.09
153	Dr	-1.34475	36.76597	35	1795.1	NE	24	1/19/2019 2:28	1547897294	0.9	9.72	1.66	9	-3.2	6	0.28
154	Dr	-1.3443	36.76617	26	1798.5	NE	22	1/19/2019 2:28	1547897300	0.9	7.22	-2.5	-2	3.4	6	-0.42
155	Dr	-1.34381	36.76634	25	1798.9	NE	19	1/19/2019 2:28	1547897310	0.9	6.94	-0.28	-3	0.4	10	-0.03
156	Dr	-1.34336	36.76648	35	1797.5	NE	19	1/19/2019 2:28	1547897316	0.9	9.72	2.78	0	-1.4	6	0.46
157	Dr	-1.3429	36.76662	28	1795.1	NE	13	1/19/2019 2:28	1547897322	0.9	7.78	-1.94	-6	-2.4	6	-0.32
158	Dr	-1.34278	36.76662	26	1794.5	NW	359	1/19/2019 2:28	1547897324	0.9	7.22	-0.56	346	-0.6	2	-0.28

159	Dr	-1.34247	36.7666	24	1792.9	NE	2	1/19/2019 2:28	1547897329	0.9	6.67	-0.55	-357	-1.6	5	-0.11
160	Dr	-1.34237	36.76665	23	1792.8	NE	32	1/19/2019 2:28	1547897331	0.9	6.39	-0.28	30	-0.1	2	-0.14
161	Dr	-1.34231	36.76675	23	1793.2	NE	68	1/19/2019 2:28	1547897333	0.9	6.39	0	36	0.4	2	0
162	Dr	-1.34195	36.7681	44	1792.7	NE	68	1/19/2019 2:29	1547897348	0.9	12.22	5.83	0	-0.5	15	0.39
163	Dr	-1.34175	36.76852	47	1789	NE	61	1/19/2019 2:29	1547897352	0.9	13.06	0.84	-7	-3.7	4	0.21
164	Dr	-1.34148	36.76893	48	1787.4	NE	54	1/19/2019 2:29	1547897356	0.9	13.33	0.27	-7	-1.6	4	0.07
165	Dr	-1.3412	36.76933	49	1786.3	NE	55	1/19/2019 2:29	1547897360	0.9	13.61	0.28	1	-1.1	4	0.07
166	Dr	-1.34089	36.76978	41	1785.7	NE	57	1/19/2019 2:29	1547897365	0.9	11.39	-2.22	2	-0.6	5	-0.44
167	Dr	-1.34063	36.77017	37	1785.2	NE	56	1/19/2019 2:29	1547897370	0.9	10.28	-1.11	-1	-0.5	5	-0.22
168	Dr	-1.34031	36.77058	30	1785.7	NE	53	1/19/2019 2:29	1547897379	0.9	8.33	-1.95	-3	0.5	9	-0.22
169	Dr	-1.33999	36.771	28	1785.3	NE	50	1/19/2019 2:29	1547897387	0.9	7.78	-0.55	-3	-0.4	8	-0.07
170	Dr	-1.33966	36.77143	40	1785.7	NE	52	1/19/2019 2:29	1547897393	0.9	11.11	3.33	2	0.4	6	0.56
171	Dr	-1.33872	36.77261	34	1785.9	NE	54	1/19/2019 2:30	1547897408	0.9	9.44	-1.67	2	0.2	15	-0.11
172	Dr	-1.33841	36.77302	17	1780.1	NE	54	1/19/2019 2:30	1547897417	0.9	4.72	-4.72	0	-5.8	9	-0.52
173	Dr	-1.33812	36.77341	36	1781.3	NE	52	1/19/2019 2:30	1547897425	0.9	10	5.28	-2	1.2	8	0.66
174	Dr	-1.33777	36.77385	50	1779.3	NE	53	1/19/2019 2:30	1547897430	0.9	13.89	3.89	1	-2	5	0.78
175	Dr	-1.33744	36.7743	59	1777.6	NE	53	1/19/2019 2:30	1547897434	0.9	16.39	2.5	0	-1.7	4	0.63
176	Dr	-1.33716	36.77467	63	1776.6	NE	52	1/19/2019 2:30	1547897437	0.9	17.5	1.11	-1	-1	3	0.37
177	Dr	-1.33685	36.77504	66	1776.5	NE	51	1/19/2019 2:30	1547897440	0.9	18.33	0.83	-1	-0.1	3	0.28
178	Dr	-1.33654	36.77544	67	1777.1	NE	52	1/19/2019 2:30	1547897443	0.9	18.61	0.28	1	0.6	3	0.09
179	Dr	-1.33622	36.77585	69	1778.5	NE	53	1/19/2019 2:30	1547897446	0.9	19.17	0.56	1	1.4	3	0.19
180	Dr	-1.33565	36.77673	69	1783.6	NE	59	1/19/2019 2:30	1547897452	1	19.17	0	6	5.1	6	0
181	Dr	-1.3342	36.77927	70	1774.8	NE	61	1/19/2019 2:31	1547897469	0.9	19.44	0.27	2	-8.8	17	0.02
182	Dr	-1.33395	36.77972	70	1773.2	NE	61	1/19/2019 2:31	1547897472	0.9	19.44	0	0	-1.6	3	0
183	Dr	-1.33371	36.78014	63	1771.5	NE	61	1/19/2019 2:31	1547897475	0.9	17.5	-1.94	0	-1.7	3	-0.65
184	Dr	-1.33345	36.78061	51	1769.5	NE	62	1/19/2019 2:31	1547897479	0.9	14.17	-3.33	1	-2	4	-0.83
185	Dr	-1.3332	36.78107	24	1767.2	NE	61	1/19/2019 2:31	1547897486	0.9	6.67	-7.5	-1	-2.3	7	-1.07
186	Dr	-1.33293	36.7815	31	1766.1	NE	46	1/19/2019 2:31	1547897493	0.9	8.61	1.94	-15	-1.1	7	0.28
187	Dr	-1.33277	36.78153	31	1765.7	NE	8	1/19/2019 2:31	1547897495	0.9	8.61	0	-38	-0.4	2	0
188	Dr	-1.33261	36.78149	32	1764.4	NW	341	1/19/2019 2:31	1547897497	0.9	8.89	0.28	333	-1.3	2	0.14
189	Dr	-1.33245	36.78141	36	1763.3	NW	335	1/19/2019 2:31	1547897499	0.9	10	1.11	-6	-1.1	2	0.56
190	Dr	-1.332	36.78118	41	1760.4	NW	334	1/19/2019 2:31	1547897504	0.9	11.39	1.39	-1	-2.9	5	0.28
191	Dr	-1.33155	36.78096	39	1758.8	NW	335	1/19/2019 2:31	1547897509	0.9	10.83	-0.56	1	-1.6	5	-0.11
192	Dr	-1.33114	36.78074	35	1758.9	NW	334	1/19/2019 2:31	1547897514	0.9	9.72	-1.11	-1	0.1	5	-0.22
193	Dr	-1.3305	36.7804	14	1765	NW	337	1/19/2019 2:32	1547897529	0.9	3.89	-5.83	3	6.1	15	-0.39
194	Dr	-1.32998	36.78024	24	1768.2	NW	343	1/19/2019 2:32	1547897540	0.9	6.67	2.78	6	3.2	11	0.25
195	Dr	-1.32946	36.78011	19	1764.6	NW	350	1/19/2019 2:32	1547897555	0.9	5.28	-1.39	7	-3.6	15	-0.09
196	Dr	-1.32892	36.78005	24	1764.2	NW	354	1/19/2019 2:32	1547897564	0.9	6.67	1.39	4	-0.4	9	0.15
197	Dr	-1.32841	36.78001	35	1764	NW	359	1/19/2019 2:32	1547897571	0.9	9.72	3.05	5	-0.2	7	0.44
198	Dr	-1.32823	36.78001	36	1763.7	N	0	1/19/2019 2:32	1547897573	0.9	10	0.28	-359	-0.3	2	0.14
199	Dr	-1.32794	36.78001	40	1763	NE	3	1/19/2019 2:32	1547897576	0.9	11.11	1.11	3	-0.7	3	0.37
200	Dr	-1.32664	36.78029	34	1762.1	NE	21	1/19/2019 2:33	1547897590	0.9	9.44	-1.67	18	-0.9	14	-0.12
201	Dr	-1.32637	36.78033	27	1761.8	NW	356	1/19/2019 2:33	1547897594	0.9	7.5	-1.94	335	-0.3	4	-0.49
202	Dr	-1.3262	36.78021	21	1762.1	NW	306	1/19/2019 2:33	1547897598	0.9	5.83	-1.67	-50	0.3	4	-0.42
203	Dr	-1.32587	36.77996	16	1765.1	NW	355	1/19/2019 2:33	1547897609	0.9	4.44	-1.39	49	3	11	-0.13
204	Dr	-1.32579	36.77996	15	1765.4	NW	359	1/19/2019 2:33	1547897611	0.9	4.17	-0.27	4	0.3	2	-0.14
205	Dr	-1.32572	36.77996	14	1765.7	NE	1	1/19/2019 2:33	1547897613	0.9	3.89	-0.28	-358	0.3	2	-0.14
206	Dr	-1.32529	36.77997	16	1763.1	NE	1	1/19/2019 2:33	1547897623	0.9	4.44	0.55	0	-2.6	10	0.06
207	Dr	-1.32511	36.77997	15	1761.9	NW	358	1/19/2019 2:33	1547897628	0.9	4.17	-0.27	357	-1.2	5	-0.05
208	Dr	-1.32499	36.77996	17	1761.6	NE	1	1/19/2019 2:33	1547897631	0.9	4.72	0.55	-357	-0.3	3	0.18
209	Dr	-1.32484	36.77996	19	1761.1	N	360	1/19/2019 2:33	1547897634	0.9	5.28	0.56	359	-0.5	3	0.19
210	Dr	-1.32474	36.77996	21	1760.9	NW	358	1/19/2019 2:33	1547897636	0.9	5.83	0.55	-2	-0.2	2	0.28
211	Dr	-1.32399	36.77994	19	1761.1	N	360	1/19/2019 2:34	1547897650	0.9	5.28	-0.55	2	0.2	14	-0.04
212	Dr	-1.32369	36.77988	10	1763.2	NW	308	1/19/2019 2:34	1547897658	0.9	2.78	-2.5	-52	2.1	8	-0.31

Table 0.17. Agent Training Data Points for Sample Route

dbID	Lat	Lon	Speed	ChgSpeed	Chg Time	ChgAlt	ChgDir	avgnormaccl	Avg harshaccl	Avg normbrake	Avg harshbrake	Avg normcorner	Avg harshcorner	Avg meander	avgstraight	avguphill	avgdownhill
38	-1.39933	36.79036	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
39	-1.39933	36.79036	0	0	-37430	2	0	0	0	0	0	0	0	0	0	0	0
40	-1.39934	36.79033	4	4	2715	7	208	0	0	0	0	0	0	0	0	0	0
41	-1.39933	36.79033	3	3	918	5	121	0	0	0	0	0	0	0	0	0	0
42	-1.39946	36.78988	17	17	40165	-9	101	0.27	0.02	0.05	0.02	0.03	0.03	0.02	0.08	0	0.1
43	-1.39971	36.78944	13	13	40177	-11	101	0.52	0.04	0.1	0.04	0.06	0.06	0.04	0.16	0.02	0.18
44	-1.39991	36.78923	14	10	40	-23	-139	0.79	0.05	0.14	0.07	0.09	0.09	0.06	0.24	0.02	0.28
45	-1.40011	36.78917	12	9	41	-19	-44	0.99	0.08	0.18	0.1	0.12	0.12	0.08	0.32	0.1	0.3
46	-1.40016	36.78909	11	-6	29	-4	16	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.18	0.32
47	-1.4001	36.78895	3	-10	63	26	93	0.999	0.12	0.23	0.12	0.16	0.14	0.16	0.34	0.28	0.22
48	-1.39995	36.7888	12	-2	64	29	63	0.999	0.11	0.23	0.12	0.15	0.15	0.22	0.28	0.28	0.22
49	-1.40012	36.78824	6	-6	75	23	34	0.999	0.11	0.23	0.12	0.15	0.15	0.22	0.28	0.3	0.2
50	-1.4003	36.78773	18	7	87	18	-4	0.999	0.09	0.25	0.1	0.15	0.15	0.22	0.28	0.24	0.26
51	-1.40046	36.78726	28	25	49	-9	-81	0.999	0.08	0.25	0.1	0.15	0.15	0.22	0.28	0.24	0.26
52	-1.40065	36.78678	30	18	47	-6	-20	0.999	0.07	0.26	0.09	0.14	0.16	0.16	0.34	0.16	0.34
53	-1.40084	36.78634	33	27	36	-5	-4	0.999	0.07	0.26	0.09	0.15	0.15	0.1	0.4	0.16	0.34
54	-1.40107	36.78588	34	16	27	1	-7	0.999	0.06	0.25	0.1	0.15	0.15	0.1	0.4	0.22	0.28
55	-1.4013	36.78539	36	8	25	-1	-5	0.999	0.06	0.25	0.1	0.15	0.15	0.1	0.4	0.22	0.28
56	-1.40167	36.78425	32	2	32	3	16	0.999	0.08	0.25	0.1	0.15	0.15	0.1	0.4	0.22	0.28
57	-1.40154	36.78377	36	3	32	5	58	0.999	0.08	0.24	0.11	0.15	0.15	0.1	0.4	0.28	0.22
58	-1.40121	36.7834	39	5	31	6	70	0.999	0.09	0.22	0.13	0.15	0.15	0.1	0.4	0.34	0.16
59	-1.40093	36.78311	40	4	29	8	69	0.999	0.1	0.21	0.14	0.15	0.15	0.1	0.4	0.34	0.16
60	-1.40079	36.78296	41	9	17	5	47	0.999	0.11	0.19	0.16	0.15	0.15	0.1	0.4	0.4	0.1
61	-1.40043	36.78258	43	7	16	4	11	0.999	0.08	0.15	0.13	0.12	0.12	0.08	0.32	0.32	0.08
62	-1.40005	36.78221	43	4	16	2	1	0.75	0.06	0.11	0.1	0.09	0.09	0.06	0.24	0.24	0.06
63	-1.39967	36.78183	42	2	17	0	0	0.7	0.07	0.11	0.1	0.09	0.09	0.06	0.24	0.24	0.06
64	-1.39929	36.78144	44	3	20	3	1	0.7	0.07	0.11	0.1	0.09	0.09	0.06	0.24	0.24	0.06
65	-1.39892	36.78104	43	0	20	4	-2	0.65	0.08	0.12	0.09	0.09	0.09	0.06	0.24	0.24	0.06
66	-1.39771	36.77977	46	3	31	7	1	0.92	0.1	0.16	0.12	0.12	0.12	0.08	0.32	0.32	0.08
67	-1.39738	36.77944	47	5	30	6	2	0.999	0.11	0.21	0.14	0.15	0.15	0.1	0.4	0.34	0.16
68	-1.3967	36.77875	36	-8	34	5	0	0.999	0.11	0.21	0.14	0.15	0.15	0.1	0.4	0.34	0.16
69	-1.39651	36.77857	10	-33	38	3	-307	0.999	0.12	0.21	0.14	0.14	0.16	0.16	0.34	0.34	0.16
70	-1.39634	36.77874	24	-22	27	0	-264	0.999	0.11	0.22	0.13	0.13	0.17	0.22	0.28	0.28	0.22
71	-1.39603	36.77916	38	-9	29	0	-264	0.999	0.1	0.23	0.12	0.13	0.17	0.22	0.28	0.22	0.28
72	-1.39571	36.77959	44	8	25	-1	-260	0.999	0.11	0.22	0.13	0.13	0.17	0.22	0.28	0.28	0.22
73	-1.3954	36.77993	47	37	20	-2	38	0.999	0.09	0.22	0.13	0.13	0.17	0.22	0.28	0.22	0.28
74	-1.39499	36.78019	47	23	19	-2	-23	0.999	0.06	0.18	0.1	0.11	0.13	0.14	0.26	0.14	0.26
75	-1.39477	36.78029	47	9	15	-3	-28	0.82	0.05	0.14	0.07	0.09	0.09	0.06	0.24	0.12	0.18
76	-1.39332	36.78114	44	0	24	-12	-9	0.72	0.07	0.12	0.09	0.09	0.09	0.06	0.24	0.1	0.2
77	-1.39296	36.78156	44	-3	25	-10	2	0.47	0.05	0.09	0.05	0.06	0.06	0.04	0.16	0.02	0.18
78	-1.39255	36.78191	44	-3	26	-7	9	0.2	0.03	0.04	0.03	0.03	0.03	0.02	0.08	0	0.1
79	-1.39211	36.78217	36	-11	29	-7	3	0.45	0.05	0.09	0.05	0.06	0.06	0.04	0.16	0.02	0.18
80	-1.39193	36.7822	14	-30	19	-1	307	0.7	0.07	0.14	0.07	0.08	0.1	0.12	0.18	0.04	0.26
81	-1.3919	36.78215	12	-32	16	-5	241	0.75	0.06	0.15	0.06	0.07	0.11	0.18	0.12	0.06	0.24
82	-1.39199	36.78191	24	-20	16	-14	212	0.97	0.09	0.19	0.09	0.1	0.14	0.2	0.2	0.06	0.34
83	-1.39214	36.78147	30	-6	17	-23	227	0.999	0.1	0.23	0.12	0.13	0.17	0.22	0.28	0.06	0.44
84	-1.39229	36.78096	19	5	25	-23	-96	0.999	0.1	0.23	0.12	0.13	0.17	0.22	0.28	0.06	0.44
85	-1.39257	36.78021	27	15	38	-25	-40	0.999	0.09	0.24	0.11	0.14	0.16	0.16	0.34	0.06	0.44
86	-1.39278	36.77971	32	8	40	-23	0	0.999	0.08	0.24	0.11	0.15	0.15	0.1	0.4	0.06	0.44
87	-1.39296	36.77923	11	-19	48	-15	-3	0.999	0.08	0.25	0.1	0.15	0.15	0.1	0.4	0.08	0.42
88	-1.39307	36.77873	20	1	50	0	5	0.999	0.07	0.26	0.09	0.15	0.15	0.1	0.4	0.18	0.32
89	-1.39305	36.77817	23	-4	46	9	34	0.999	0.07	0.26	0.09	0.15	0.15	0.1	0.4	0.24	0.26
90	-1.39252	36.77715	37	5	53	23	54	0.999	0.07	0.26	0.09	0.15	0.15	0.1	0.4	0.32	0.18
91	-1.39224	36.77673	39	28	44	29	51	0.999	0.08	0.24	0.11	0.15	0.15	0.1	0.4	0.38	0.12
92	-1.39198	36.77633	39	19	35	21	42	0.999	0.06	0.19	0.09	0.12	0.12	0.08	0.32	0.36	0.04
93	-1.39172	36.77593	39	16	29	19	22	0.82	0.05	0.14	0.07	0.09	0.09	0.06	0.24	0.26	0.04
94	-1.39148	36.77552	36	-1	20	13	-5	0.75	0.06	0.13	0.08	0.09	0.09	0.06	0.24	0.26	0.04
95	-1.39112	36.7746	34	-5	27	18	-19	0.7	0.07	0.13	0.08	0.09	0.09	0.06	0.24	0.26	0.04
96	-1.39107	36.77413	38	-1	27	17	-27	0.7	0.07	0.13	0.08	0.09	0.09	0.06	0.24	0.26	0.04
97	-1.39105	36.77367	35	-4	27	14	-27	0.9	0.1	0.17	0.11	0.12	0.12	0.08	0.32	0.34	0.06
98	-1.39102	36.77265	31	-5	40	9	-27	0.999	0.12	0.22	0.13	0.15	0.15	0.1	0.4	0.36	0.14
99	-1.39097	36.77214	35	1	34	3	-9	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.36	0.14
100	-1.39093	36.77168	39	1	34	3	0	0.999	0.11	0.21	0.14	0.15	0.15	0.1	0.4	0.34	0.16
101	-1.39089	36.77119	39	4	34	3	1	0.97	0.09	0.17	0.11	0.12	0.12	0.08	0.32	0.26	0.14
102	-1.39082	36.77072	38	7	21	7	5	0.97	0.09	0.17	0.11	0.12	0.12	0.08	0.32	0.26	0.14
103	-1.39077	36.77025	19	-16	22	8	4	0.92	0.1	0.16	0.12	0.12	0.12	0.08	0.32	0.32	0.08
104	-1.39075	36.76977	26	-13	25	6	-6	0.65	0.08	0.12	0.09	0.09	0.09	0.06	0.24	0.24	0.06
105	-1.39075	36.76925	26	-13	28	-1	-12	0.4	0.06	0.08	0.06	0.06	0.06	0.04	0.16	0.16	0.04
106	-1.39081	36.76811	30	-8	39	-11	-9	0.67	0.08	0.13	0.08	0.09	0.09	0.06	0.24	0.16	0.14
107	-1.39079	36.76756	32	13	39	-17	0	0.77	0.06	0.14	0.07	0.09	0.09	0.06	0.24	0.1	0.2
108	-1.39062	36.76707	12	-14	43	-17	22	0.82	0.05	0.15	0.06	0.09	0.09	0.06	0.24	0.04	0.26
109	-1.39053	36.76697	3	-23	51	-11	70	0.999	0.07	0.2	0.08	0.12	0.12	0.08	0.32	0.06	0.34
110	-1.39048	36.76696	10	-20	39	-5	-257	0.999	0.08	0.25	0.1	0.14	0.16	0.16	0.34	0.08	0.42
111	-1.39013	36.7672	33	1	39	-4	-239	0.999	0.08	0.25	0.1	0.14	0.16	0.16	0.34	0.1	0.4
112	-1.3891	36.76838	48	36	41	-8	-226	0.999	0.08	0.25	0.1	0.14	0.16	0.16	0.34	0.1	0.4
113	-1.38892	36.76882	46	43	29	-8	-266	0.999	0.08	0.25	0.1	0.14	0.16	0.16	0.34	0.1	0.4
114	-1.38869	36.76928	39	29	30	-7	45	0.999	0.06	0.2	0.08	0.11	0.13	0.14	0.26	0.08	0.32
115	-1.38833	36.76967	33	0	29	-4	7	0.999	0.07	0.2	0.08	0.12	0.12	0.08	0.32	0.14	0.26

116	-1.38796	36.77002	29	-19	22	3	-20	0.95	0.09	0.18	0.1	0.12	0.12	0.08	0.32	0.2	0.2
117	-1.38757	36.77041	33	-13	25	7	-23	0.92	0.1	0.18	0.1	0.12	0.12	0.08	0.32	0.26	0.14
118	-1.38716	36.77076	29	-10	27	9	-16	0.87	0.11	0.17	0.11	0.12	0.12	0.08	0.32	0.32	0.08
119	-1.38675	36.77102	26	-7	29	14	-19	0.999	0.13	0.22	0.13	0.15	0.15	0.1	0.4	0.42	0.08
120	-1.38662	36.77107	26	-3	24	12	-25	0.92	0.1	0.18	0.1	0.12	0.12	0.08	0.32	0.34	0.06
121	-1.38341	36.77075	37	4	52	11	307	0.99	0.08	0.18	0.1	0.11	0.13	0.14	0.26	0.34	0.06
122	-1.38293	36.77068	24	-5	55	3	312	0.92	0.1	0.18	0.1	0.11	0.13	0.14	0.26	0.26	0.14
123	-1.38246	36.77062	28	2	55	-4	326	0.999	0.08	0.19	0.09	0.11	0.13	0.14	0.26	0.2	0.2
124	-1.38199	36.77055	34	8	59	-4	331	0.999	0.07	0.19	0.09	0.11	0.13	0.14	0.26	0.18	0.22
125	-1.38083	36.77038	19	-18	39	-6	1	0.999	0.1	0.23	0.12	0.14	0.16	0.16	0.34	0.26	0.24
126	-1.38036	36.77031	28	4	37	5	-1	0.999	0.1	0.23	0.12	0.15	0.15	0.1	0.4	0.26	0.24
127	-1.37987	36.77025	36	8	35	8	-1	0.999	0.09	0.23	0.12	0.15	0.15	0.1	0.4	0.34	0.16
128	-1.37938	36.77019	41	7	34	8	0	0.999	0.1	0.21	0.14	0.15	0.15	0.1	0.4	0.4	0.1
129	-1.37887	36.77011	41	22	24	10	-1	0.99	0.08	0.17	0.11	0.12	0.12	0.08	0.32	0.32	0.08
130	-1.37839	36.77004	38	10	21	9	1	0.99	0.08	0.17	0.11	0.12	0.12	0.08	0.32	0.32	0.08
131	-1.37785	36.76997	36	0	21	14	-1	0.97	0.09	0.17	0.11	0.12	0.12	0.08	0.32	0.34	0.06
132	-1.37735	36.76989	25	-16	23	19	0	0.95	0.09	0.18	0.1	0.12	0.12	0.08	0.32	0.36	0.04
133	-1.37636	36.76977	33	-8	36	21	-3	0.97	0.09	0.19	0.09	0.12	0.12	0.08	0.32	0.36	0.04
134	-1.37592	36.76969	36	-2	36	28	-1	0.999	0.1	0.23	0.12	0.15	0.15	0.1	0.4	0.46	0.04
135	-1.37543	36.76962	41	5	35	26	0	0.999	0.09	0.23	0.12	0.15	0.15	0.1	0.4	0.46	0.04
136	-1.37491	36.76955	42	17	33	21	0	0.999	0.09	0.21	0.14	0.15	0.15	0.1	0.4	0.44	0.06
137	-1.37436	36.76946	45	12	20	16	-2	0.999	0.09	0.21	0.14	0.15	0.15	0.1	0.4	0.36	0.14
138	-1.37391	36.76934	47	11	19	5	-8	0.999	0.09	0.21	0.14	0.15	0.15	0.1	0.4	0.3	0.2
139	-1.37337	36.76916	44	3	19	-2	-11	0.999	0.09	0.21	0.14	0.15	0.15	0.1	0.4	0.22	0.28
140	-1.37287	36.76895	44	2	19	-2	-16	0.999	0.07	0.18	0.1	0.12	0.12	0.08	0.32	0.14	0.26
141	-1.37238	36.76871	43	-2	19	5	-13	0.999	0.07	0.19	0.09	0.12	0.12	0.08	0.32	0.16	0.24
142	-1.3719	36.76847	42	-5	20	12	-10	0.999	0.08	0.2	0.08	0.12	0.12	0.08	0.32	0.24	0.16
143	-1.37143	36.76823	42	-2	20	19	-7	0.75	0.06	0.15	0.06	0.09	0.09	0.06	0.24	0.22	0.08
144	-1.37009	36.76757	43	-1	29	23	0	0.8	0.05	0.15	0.06	0.09	0.09	0.06	0.24	0.3	0
145	-1.36958	36.76743	42	-1	29	17	19	0.999	0.08	0.19	0.09	0.12	0.12	0.08	0.32	0.38	0.02
146	-1.36904	36.76746	43	1	29	7	-325	0.999	0.08	0.19	0.09	0.11	0.13	0.14	0.26	0.3	0.1
147	-1.36849	36.76757	45	3	29	0	-321	0.999	0.07	0.19	0.09	0.11	0.13	0.14	0.26	0.22	0.18
148	-1.36795	36.76765	42	-1	20	-6	-334	0.999	0.09	0.24	0.11	0.14	0.16	0.16	0.34	0.24	0.26
149	-1.36742	36.76758	43	1	20	-7	-7	0.999	0.1	0.23	0.12	0.13	0.17	0.22	0.28	0.16	0.34
150	-1.36647	36.76711	40	-3	25	-1	323	0.999	0.1	0.23	0.12	0.13	0.17	0.22	0.28	0.16	0.34
151	-1.36604	36.76686	25	-20	28	0	319	0.999	0.1	0.23	0.12	0.14	0.16	0.16	0.34	0.16	0.34
152	-1.36585	36.76675	32	-10	26	0	330	0.999	0.1	0.23	0.12	0.14	0.16	0.16	0.34	0.16	0.34
153	-1.36469	36.7661	36	-7	35	-7	-14	0.999	0.1	0.23	0.12	0.14	0.16	0.16	0.34	0.14	0.36
154	-1.36427	36.76586	17	-23	33	-6	-3	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.2	0.3
155	-1.36384	36.76554	30	5	34	-3	-13	0.999	0.1	0.23	0.12	0.15	0.15	0.1	0.4	0.2	0.3
156	-1.36348	36.76522	34	2	37	2	-14	0.999	0.09	0.22	0.13	0.15	0.15	0.1	0.4	0.26	0.24
157	-1.36307	36.76484	40	4	29	14	-14	0.999	0.09	0.22	0.13	0.15	0.15	0.1	0.4	0.32	0.18
158	-1.3627	36.76451	39	22	26	14	-10	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.4	0.1
159	-1.36232	36.76416	41	11	22	13	0	0.999	0.1	0.21	0.14	0.15	0.15	0.1	0.4	0.4	0.1
160	-1.36194	36.76379	43	9	21	10	-1	0.999	0.1	0.2	0.15	0.15	0.15	0.1	0.4	0.4	0.1
161	-1.36086	36.76288	40	0	29	7	10	0.999	0.12	0.2	0.15	0.15	0.15	0.1	0.4	0.4	0.1
162	-1.36037	36.7627	43	4	29	5	28	0.999	0.12	0.19	0.16	0.15	0.15	0.1	0.4	0.4	0.1
163	-1.35983	36.76264	43	2	29	0	38	0.95	0.09	0.15	0.13	0.12	0.12	0.08	0.32	0.32	0.08
164	-1.3593	36.76261	42	-1	29	-3	40	0.95	0.09	0.16	0.12	0.12	0.12	0.08	0.32	0.26	0.14
165	-1.35877	36.76258	42	2	20	-6	29	0.7	0.07	0.13	0.08	0.09	0.09	0.06	0.24	0.18	0.12
166	-1.35825	36.76255	41	-2	20	-8	10	0.75	0.06	0.14	0.07	0.09	0.09	0.06	0.24	0.12	0.18
167	-1.35773	36.76248	41	-2	20	-5	-7	0.5	0.04	0.1	0.04	0.06	0.06	0.04	0.16	0.04	0.16
168	-1.35723	36.76236	41	-1	20	-4	-10	0.5	0.04	0.1	0.04	0.06	0.06	0.04	0.16	0.04	0.16
169	-1.35677	36.76226	33	-9	20	-3	-11	0.5	0.04	0.1	0.04	0.06	0.06	0.04	0.16	0.04	0.16
170	-1.35557	36.76196	17	-24	35	0	-10	0.7	0.07	0.14	0.07	0.09	0.09	0.06	0.24	0.12	0.18
171	-1.35501	36.76186	35	-6	39	-1	5	0.75	0.06	0.14	0.07	0.09	0.09	0.06	0.24	0.12	0.18
172	-1.35482	36.76186	39	-2	36	0	-346	0.999	0.08	0.19	0.09	0.11	0.13	0.14	0.26	0.14	0.26
173	-1.3545	36.76191	45	12	34	-2	-332	0.999	0.09	0.24	0.11	0.14	0.16	0.16	0.34	0.16	0.34
174	-1.354	36.76211	56	39	18	-7	-322	0.999	0.09	0.23	0.12	0.14	0.16	0.16	0.34	0.16	0.34
175	-1.35346	36.76237	60	25	13	-9	-329	0.999	0.07	0.24	0.11	0.14	0.16	0.16	0.34	0.1	0.4
176	-1.35306	36.76257	59	20	14	-8	25	0.999	0.09	0.22	0.13	0.14	0.16	0.16	0.34	0.16	0.34
177	-1.35262	36.76278	45	0	15	-1	8	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.22	0.28
178	-1.35215	36.76289	36	-20	16	9	-12	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.3	0.2
179	-1.35165	36.76296	34	-26	18	16	-14	0.999	0.13	0.22	0.13	0.15	0.15	0.1	0.4	0.36	0.14
180	-1.35117	36.7631	34	-25	21	19	-6	0.85	0.11	0.17	0.11	0.12	0.12	0.08	0.32	0.34	0.06
181	-1.34988	36.76399	55	10	31	10	13	0.95	0.09	0.18	0.1	0.12	0.12	0.08	0.32	0.28	0.12
182	-1.34938	36.76433	61	25	30	-1	23	0.999	0.08	0.19	0.09	0.12	0.12	0.08	0.32	0.22	0.18
183	-1.34898	36.76457	59	25	27	-6	16	0.999	0.08	0.19	0.09	0.12	0.12	0.08	0.32	0.14	0.26
184	-1.34848	36.76475	47	13	25	-8	-4	0.999	0.08	0.19	0.09	0.12	0.12	0.08	0.32	0.14	0.26
185	-1.34797	36.76489	41	-14	16	0	-18	0.999	0.11	0.23	0.12	0.15	0.15	0.1	0.4	0.22	0.28
186	-1.34748	36.76506	43	-18	17	9	-15	0.999	0.12	0.21	0.14	0.15	0.15	0.1	0.4	0.28	0.22
187	-1.34698	36.76524	43	-16	19	11	-6	0.9	0.1	0.17	0.11	0.12	0.12	0.08	0.32	0.26	0.14
188	-1.34651	36.7654	15	-32	24	9	3	0.85	0.11	0.16	0.12	0.12	0.12	0.08	0.32	0.32	0.08
189	-1.346	36.76558	24	-17	29	5	3	0.95	0.09	0.17	0.11	0.12	0.12	0.08	0.32	0.26	0.14
190	-1.34522	36.76583	29	-14	39	0	-5	0.999	0.07	0.18	0.1	0.12	0.12	0.08	0.32	0.2	0.2
191	-1.34475	36.76597	35	-8	40	-5	3	0.999	0.06	0.2	0.08	0.12	0.12	0.08	0.32	0.14	0.26
192	-1.3443	36.76617	26	11	37	-2	2	0.999	0.09	0.24	0.11	0.15	0.15	0.1	0.4	0.22	0.28
193	-1.34381	36.76634	25	1	37	-1	-1	0.999	0.09	0.24	0.11	0.15	0.15	0.1	0.4	0.22	0.28
194	-1.34336	36.76648	35	6	28	-1	4	0.999	0.09	0.24	0.11	0.15	0.15	0.1	0.4	0.22	0.28
195	-1.3429	36.76662	28	-7	28	0	-11	0.999	0.1	0.24	0.11	0.15	0.15	0.1	0.4	0.22	0.28
196	-1.34278	36.76662	26	0	24	-4	337	0.999	0.11	0.23	0.12	0.14	0.16	0.16	0.34	0.22	0.28
197	-1.34247	36.7666	24	-1	19	-6	-17	0.999	0.1	0.24	0.11	0.13	0.17	0.22	0.28	0.16	0.34
198	-1.34237	36.76665	23	-12	15	-5	13	0.999	0.09	0.25	0.1	0.13	0.17	0.22	0.28	0.1	0.4
199	-1.34231	36.76675	23	-5	11	-2	55	0.999	0.08	0.2	0.08	0.1	0.14	0.2	0.2	0.08	0.32

200	-1.34195	36.7681	44	18	24	-2	-292	0.999	0.07	0.2	0.08	0.1	0.14	0.2	0.2	0.08	0.32
201	-1.34175	36.76852	47	23	23	-4	59	0.999	0.07	0.2	0.08	0.11	0.13	0.14	0.26	0.08	0.32
202	-1.34148	36.76893	48	25	25	-5	22	0.999	0.06	0.2	0.08	0.12	0.12	0.08	0.32	0.08	0.32
203	-1.3412	36.76933	49	26	27	-7	-13	0.999	0.06	0.19	0.09	0.12	0.12	0.08	0.32	0.08	0.32
204	-1.34089	36.76978	41	-3	17	-7	-11	0.999	0.08	0.24	0.11	0.15	0.15	0.1	0.4	0.1	0.4
205	-1.34063	36.77017	37	-10	18	-4	-5	0.999	0.09	0.24	0.11	0.15	0.15	0.1	0.4	0.1	0.4
206	-1.34031	36.77058	30	-18	23	-2	-2	0.999	0.1	0.23	0.12	0.15	0.15	0.1	0.4	0.16	0.34
207	-1.33999	36.771	28	-21	27	-1	-5	0.999	0.11	0.24	0.11	0.15	0.15	0.1	0.4	0.16	0.34
208	-1.33966	36.77143	40	-1	28	0	-5	0.999	0.11	0.24	0.11	0.15	0.15	0.1	0.4	0.22	0.28
209	-1.33872	36.77261	34	-3	38	1	-2	0.999	0.12	0.23	0.12	0.15	0.15	0.1	0.4	0.28	0.22
210	-1.33841	36.77302	17	-13	38	-6	1	0.999	0.13	0.22	0.13	0.15	0.15	0.1	0.4	0.26	0.24
211	-1.33812	36.77341	36	8	38	-4	2	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.26	0.24
212	-1.33777	36.77385	50	10	37	-6	1	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.26	0.24
213	-1.33744	36.7743	59	25	26	-8	-1	0.999	0.11	0.22	0.13	0.15	0.15	0.1	0.4	0.2	0.3
214	-1.33716	36.77467	63	46	20	-4	-2	0.999	0.09	0.22	0.13	0.15	0.15	0.1	0.4	0.14	0.36
215	-1.33685	36.77504	66	30	15	-5	-1	0.999	0.08	0.23	0.12	0.15	0.15	0.1	0.4	0.16	0.34
216	-1.33654	36.77544	67	17	13	-2	-1	0.999	0.08	0.22	0.13	0.15	0.15	0.1	0.4	0.16	0.34
217	-1.33622	36.77585	69	10	12	1	0	0.999	0.09	0.21	0.14	0.15	0.15	0.1	0.4	0.22	0.28
218	-1.33565	36.77673	69	6	15	7	7	0.999	0.07	0.16	0.12	0.12	0.12	0.08	0.32	0.2	0.2
219	-1.3342	36.77927	70	4	29	-2	10	0.999	0.07	0.16	0.12	0.12	0.12	0.08	0.32	0.18	0.22
220	-1.33395	36.77972	70	3	29	-4	9	0.77	0.06	0.12	0.09	0.09	0.09	0.06	0.24	0.16	0.14
221	-1.33371	36.78014	63	-6	29	-7	8	0.77	0.06	0.13	0.08	0.09	0.09	0.06	0.24	0.1	0.2
222	-1.33345	36.78061	51	-18	27	-14	3	0.77	0.06	0.15	0.06	0.09	0.09	0.06	0.24	0.04	0.26
223	-1.3332	36.78107	24	-46	17	-8	0	0.999	0.08	0.2	0.08	0.12	0.12	0.08	0.32	0.06	0.34
224	-1.33293	36.7815	31	-39	21	-7	-15	0.999	0.07	0.2	0.08	0.12	0.12	0.08	0.32	0.08	0.32
225	-1.33277	36.78153	31	-32	20	-6	-53	0.999	0.07	0.2	0.08	0.12	0.12	0.08	0.32	0.08	0.32
226	-1.33261	36.78149	32	-19	18	-5	279	0.999	0.07	0.2	0.08	0.11	0.13	0.14	0.26	0.08	0.32
227	-1.33245	36.78141	36	12	13	-4	274	0.999	0.06	0.2	0.08	0.11	0.13	0.14	0.26	0.08	0.32
228	-1.332	36.78118	41	10	11	-6	288	0.999	0.06	0.19	0.09	0.11	0.13	0.14	0.26	0.08	0.32
229	-1.33155	36.78096	39	8	14	-7	327	0.999	0.07	0.19	0.09	0.11	0.13	0.14	0.26	0.08	0.32
230	-1.33114	36.78074	35	3	17	-6	-7	0.999	0.1	0.23	0.12	0.14	0.16	0.16	0.34	0.16	0.34
231	-1.3305	36.7804	14	-22	30	2	2	0.999	0.1	0.23	0.12	0.15	0.15	0.1	0.4	0.24	0.26
232	-1.32998	36.78024	24	-17	36	8	9	0.999	0.1	0.23	0.12	0.15	0.15	0.1	0.4	0.3	0.2
233	-1.32946	36.78011	19	-20	46	6	15	0.999	0.11	0.24	0.11	0.15	0.15	0.1	0.4	0.3	0.2
234	-1.32892	36.78005	24	-11	50	5	20	0.999	0.1	0.24	0.11	0.15	0.15	0.1	0.4	0.3	0.2
235	-1.32841	36.78001	35	21	42	-1	22	0.999	0.08	0.25	0.1	0.15	0.15	0.1	0.4	0.24	0.26
236	-1.32823	36.78001	36	12	33	-5	-343	0.999	0.07	0.25	0.1	0.14	0.16	0.16	0.34	0.16	0.34
237	-1.32794	36.78001	40	21	21	-2	-347	0.999	0.07	0.25	0.1	0.14	0.16	0.16	0.34	0.1	0.4
238	-1.32664	36.78029	34	10	26	-2	-333	0.999	0.07	0.25	0.1	0.14	0.16	0.16	0.34	0.1	0.4
239	-1.32637	36.78033	27	-8	23	-2	-3	0.999	0.08	0.25	0.1	0.13	0.17	0.22	0.28	0.1	0.4
240	-1.3262	36.78021	21	-15	25	-2	306	0.999	0.1	0.23	0.12	0.12	0.18	0.28	0.22	0.16	0.34
241	-1.32587	36.77996	16	-24	33	2	352	0.999	0.12	0.23	0.12	0.12	0.18	0.28	0.22	0.22	0.28
242	-1.32579	36.77996	15	-19	21	3	338	0.999	0.13	0.22	0.13	0.12	0.18	0.28	0.22	0.28	0.22
243	-1.32572	36.77996	14	-13	19	4	-355	0.999	0.14	0.21	0.14	0.11	0.19	0.34	0.16	0.34	0.16
244	-1.32529	36.77997	16	-5	25	1	-305	0.999	0.13	0.21	0.14	0.12	0.18	0.28	0.22	0.34	0.16
245	-1.32511	36.77997	15	-1	19	-3	3	0.999	0.12	0.22	0.13	0.12	0.18	0.28	0.22	0.28	0.22
246	-1.32499	36.77996	17	2	20	-4	-358	0.999	0.11	0.23	0.12	0.12	0.18	0.28	0.22	0.22	0.28
247	-1.32484	36.77996	19	5	21	-5	359	0.999	0.09	0.24	0.11	0.11	0.19	0.34	0.16	0.16	0.34
248	-1.32474	36.77996	21	5	13	-2	357	0.999	0.08	0.24	0.11	0.12	0.18	0.28	0.22	0.1	0.4
249	-1.32399	36.77994	19	4	22	-1	2	0.999	0.1	0.23	0.12	0.12	0.18	0.28	0.22	0.16	0.34
250	-1.32369	36.77988	10	-7	27	2	307	0.999	0.11	0.22	0.13	0.12	0.18	0.28	0.22	0.22	0.28

Table 0.18. Complete Agent Actions on Test Environment in Figure 4.23

DbId	Lat	Lon	Change in Speed	Change in Time	Change in Alt	Change in Dir	Speeding	Cornering	Terrain	Rate
3	-1.39172	36.77649	15	38	-25	-40	Accelerate/Speed	Turn Left	Rolling	0
4	-1.39173	36.77652	5	25	-23	-96	Accelerate/Speed	Turn Left	Rolling	0
5	-1.39173	36.77652	5	25	-23	-96	Accelerate/Speed	Turn Left	Rolling	0
6	-1.39173	36.77652	5	25	-23	-96	Accelerate/Speed	Turn Left	Rolling	0
7	-1.3917	36.7765	5	25	-23	-96	Accelerate/Speed	Turn Left	Rolling	0
8	-1.39186	36.77631	15	38	-25	-40	Accelerate/Speed	Turn Left	Rolling	0
9	-1.39185	36.77624	15	38	-25	-40	Accelerate/Speed	Turn Left	Rolling	0
10	-1.39171	36.77596	15	38	-25	-40	Decelerate/Reduce Speed	Turn Left	Rolling	0
11	-1.39147	36.77549	8	40	-23	0	Decelerate/Reduce Speed	Straight Stretch	Flat	0
12	-1.3911	36.77428	-4	46	9	34	Decelerate/Reduce Speed	Turn Right	Climbing	0
13	-1.39106	36.77379	5	53	23	54	Accelerate/Speed	Turn Right	Climbing	0
14	-1.39103	36.7733	5	53	23	54	Accelerate/Speed	Turn Right	Climbing	0
15	-1.39103	36.77276	28	44	29	51	Accelerate/Speed	Turn Right	Climbing	0
16	-1.39099	36.77229	19	35	21	42	Decelerate/Reduce Speed	Turn Right	Climbing	0
17	-1.39088	36.77123	-1	20	13	-5	Decelerate/Reduce Speed	Turn Left	Climbing	0
18	-1.39073	36.76956	-4	27	14	-27	Accelerate/Speed	Turn Left	Climbing	0
19	-1.39076	36.76909	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
20	-1.3908	36.76859	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
21	-1.39084	36.76809	1	34	3	-9	Accelerate/Speed	Turn Left	Climbing	0
22	-1.39081	36.76756	1	34	3	0	Accelerate/Speed	Straight Stretch	Climbing	0
23	-1.39056	36.76699	4	34	3	1	Accelerate/Speed	Turn Right	Climbing	0
24	-1.3905	36.76697	4	34	3	1	Accelerate/Speed	Turn Right	Climbing	0
25	-1.3904	36.767	4	34	3	1	Accelerate/Speed	Turn Right	Climbing	0
26	-1.39011	36.76721	4	34	3	1	Decelerate/Reduce Speed	Turn Right	Climbing	0
27	-1.38974	36.76753	1	34	3	0	Decelerate/Reduce Speed	Straight Stretch	Climbing	0
28	-1.3894	36.76785	1	34	3	0	Decelerate/Reduce Speed	Straight Stretch	Climbing	0
29	-1.38912	36.76827	1	34	3	-9	Accelerate/Speed	Turn Left	Climbing	0
30	-1.38893	36.76875	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
31	-1.38869	36.76922	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
32	-1.38833	36.76957	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
33	-1.38787	36.77005	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
34	-1.38737	36.77054	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
35	-1.38697	36.77087	-5	40	9	-27	Accelerate/Speed	Turn Left	Climbing	0
36	-1.38653	36.77107	1	34	3	0	Accelerate/Speed	Straight Stretch	Climbing	0
37	-1.38607	36.77112	36	41	-8	-226	Accelerate/Speed	Turn Left	Rolling	0
38	-1.38554	36.77107	36	41	-8	-226	Accelerate/Speed	Turn Left	Rolling	0
39	-1.38501	36.77099	43	29	-8	-266	Accelerate/Speed	Turn Left	Rolling	0
40	-1.38451	36.77091	29	30	-7	45	Accelerate/Speed	Turn Right	Flat	0
41	-1.38394	36.77083	-19	22	3	-20	Accelerate/Speed	Turn Left	Climbing	0
42	-1.38341	36.77076	-13	25	7	-23	Accelerate/Speed	Turn Left	Climbing	0
43	-1.38289	36.77068	-10	27	9	-16	Accelerate/Speed	Turn Left	Climbing	0
44	-1.38236	36.77061	-7	29	14	-19	Decelerate/Reduce Speed	Turn Left	Climbing	0
45	-1.38187	36.77054	4	52	11	307	Accelerate/Speed	Turn Right	Climbing	0
46	-1.38089	36.7704	4	52	11	307	Accelerate/Speed	Turn Right	Climbing	0
47	-1.38042	36.77033	4	52	11	307	Accelerate/Speed	Turn Right	Climbing	0
48	-1.37992	36.77026	4	52	11	307	Decelerate/Reduce Speed	Turn Right	Climbing	0
49	-1.3794	36.77019	4	52	11	307	Decelerate/Reduce Speed	Turn Right	Climbing	0
50	-1.37888	36.77012	-5	55	3	312	Decelerate/Reduce Speed	Turn Right	Climbing	0
51	-1.37838	36.77005	2	55	-4	326	Decelerate/Reduce Speed	Turn Right	Flat	0
52	-1.37792	36.76998	8	59	-4	331	Accelerate/Speed	Turn Right	Flat	0
53	-1.37744	36.76991	-18	39	-6	1	Decelerate/Reduce Speed	Turn Right	Flat	0
54	-1.37634	36.76976	4	37	5	-1	Decelerate/Reduce Speed	Turn Left	Climbing	0
55	-1.37582	36.7697	8	35	8	-1	Accelerate/Speed	Turn Left	Climbing	0
56	-1.37528	36.76963	7	34	8	0	Accelerate/Speed	Straight Stretch	Climbing	0
57	-1.37477	36.76954	22	24	10	-1	Accelerate/Speed	Turn Left	Climbing	0
58	-1.37424	36.76944	10	21	9	1	Decelerate/Reduce Speed	Turn Right	Climbing	0
59	-1.37379	36.76931	0	21	14	-1	Decelerate/Reduce Speed	Turn Left	Climbing	0
60	-1.37329	36.76914	-16	23	19	0	Decelerate/Reduce Speed	Straight Stretch	Climbing	0
61	-1.37277	36.76891	-8	36	21	-3	Decelerate/Reduce Speed	Turn Left	Climbing	0
62	-1.37223	36.76864	-8	36	21	-3	Decelerate/Reduce Speed	Turn Left	Climbing	0
63	-1.37182	36.76844	-2	36	28	-1	Decelerate/Reduce Speed	Turn Left	Climbing	0
64	-1.37141	36.76823	5	35	26	0	Decelerate/Reduce Speed	Straight Stretch	Climbing	0
65	-1.36965	36.76745	3	19	-2	-11	Decelerate/Reduce Speed	Turn Left	Rolling	0
66	-1.36925	36.76743	3	19	-2	-11	Decelerate/Reduce Speed	Turn Left	Rolling	0
67	-1.36901	36.76746	2	19	-2	-16	Decelerate/Reduce Speed	Turn Left	Rolling	0
68	-1.36852	36.76756	-2	19	5	-13	Accelerate/Speed	Turn Left	Climbing	0
69	-1.36848	36.76757	-2	19	5	-13	Accelerate/Speed	Turn Left	Climbing	0
70	-1.36844	36.76757	-2	19	5	-13	Accelerate/Speed	Turn Left	Climbing	0
71	-1.36834	36.76757	-2	19	5	-13	Accelerate/Speed	Turn Left	Climbing	0
72	-1.36823	36.76748	-2	19	5	-13	Accelerate/Speed	Turn Left	Climbing	0

73	-1.3682	36.76725	-2	19	5	-13	Accelerate/Speed	Turn Left	Climbing	0
74	-1.36813	36.76673	-5	20	12	-10	Decelerate/Reduce Speed	Turn Left	Climbing	0
75	-1.36808	36.76616	-5	20	12	-10	Decelerate/Reduce Speed	Turn Left	Climbing	0
76	-1.36802	36.76563	-2	20	19	-7	Accelerate/Speed	Turn Left	Climbing	0
77	-1.36786	36.76418	-1	29	23	0	Decelerate/Reduce Speed	Straight Stretch	Climbing	0
78	-1.36787	36.76363	-1	29	17	19	Decelerate/Reduce Speed	Turn Right	Climbing	0
79	-1.3679	36.76307	-3	25	-1	323	Decelerate/Reduce Speed	Turn Right	Flat	0
80	-1.36819	36.75635	-13	38	4	81	Decelerate/Reduce Speed	Turn Right	Climbing	0
81	-1.3681	36.75633	-13	38	4	81	Accelerate/Speed	Turn Right	Climbing	0
82	-1.3676	36.75628	-13	38	4	81	Decelerate/Reduce Speed	Turn Right	Climbing	0
83	-1.36708	36.75623	-13	38	4	81	Decelerate/Reduce Speed	Turn Right	Climbing	0
84	-1.36656	36.75617	-13	38	4	81	Decelerate/Reduce Speed	Turn Right	Climbing	0
85	-1.366	36.75611	-13	38	4	81	Decelerate/Reduce Speed	Turn Right	Climbing	0

APPENDIX G: AUTHOR ACADEMIC WRITING AND PUBLICATIONS

A. Recent Peer Reviewed Journal Research Publications

Title: Real-time Driver Advisory Model: Intelligent Transportation Systems [83]

Abstract: A vehicle driver is an agent operating under partially observable, dynamic, nondeterministic and multiagent environments. This poses a challenge to drivers operating on unfamiliar roads, hence compromised road safety. It is therefore paramount to explore mechanisms for driver advisory on the status of roads ahead. This paper presents a model for providing real-time advisory alerts to drivers approaching mapped points of interest (POIs) and/or experiencing overspeeding behaviour. POIs include speed-limited zones, intersections, bumps and black spots. Determination of driver's approaching POIs used the K-Nearest Neighbour algorithm centered on the Spherical Law of Cosines. A text-to-speech Android app read text SMS alerts to avoid diversion of driver's attention. The model is kind of a Vehicular Ad-hoc Network as a low cost Vehicle-to-Driver communication using GPS, GSM and GIS. It is applicable to low-end infrastructure in developing nations. Experiments for model validation yielded positive results with success rates above 78% in terms of alert messages delivered to drivers at good distances for better reaction times. The study was carried out as a technical test of configurable technology that supports elements of Intelligent Transportation Systems, whose implementation will influence on driving behaviour, hence improving on performance and road safety.

Keywords: Intelligent Transportation Systems, VANET, Driver Advisory, Driver Assistance, GPS.

Title: Driver Behaviour Profiling Using Dynamic Bayesian Network [84]

Abstract: In the recent past, there has been a rapid increase in the number of vehicles and diversification of road networks worldwide. The biggest challenge now lies on how to monitor and analyse behaviours of vehicle drivers as a catalyst to road safety. Driver behaviour depends on the state and nature of the road, the state of the driver, vehicle conditions, and actions of other road users among other factors. This paper illustrates the ability of Dynamic Bayesian Networks towards determination of driving styles with respect to acceleration, cornering and braking patterns. Bayesian Networks are probabilistic graphical models that map a set of variables and their conditional dependencies. Sample test results showed that the 2-Time-slice Bayesian Network model is suitable for generation of driver profiles using only four GPS data parameters namely speed, altitude, direction and signal strength against time. The model classifies driver profiles into two sets of observations: driver behaviour and nature of operational environment. Adoption of the model could offer a cost effective, easy to implement and use solution that could find many applications in vehicle driver recruiting firms, vehicle insurance companies and transport and road safety authorities among other sectors.

Keywords: Driver Behaviour, Driver Profiling, GPS, Bayesian Network, Dynamic Bayesian Network, 2TBN.

Title: Shortcomings of Ultrasonic Obstacle Detection for Vehicle Driver Assistance and Profiling [81]

Abstract: Obstacle detection is a challenging problem that has attracted much attention recently, especially in the context of research in self-driving car technologies. A number of obstacle detection technologies exist. Ultrasound is among the commonly used technologies due to its low cost compared to other technologies. This paper presents some findings on the research that has been carried out by the authors with regard to vehicle driver assistance and profiling. It discusses an experiment for detection of obstacles in a vehicle driver's operational environment using ultrasound technology. Experiment results clearly depict the capabilities and limitations of ultrasound technology in detection of obstacles under motion and obstacles with varied surfaces. Ultrasound's wavelength, beam width, directionality among others are put into consideration. Pros and cons of other technologies that could replace ultrasound, for instance RADAR and LIDAR technologies are also discussed. The study recommends sensor fusion where several types of sensor technologies are combined to complement one another. The study was a technical test of configurable technology that could guide future studies on obstacle detection intending to use infrared, sound, radio or laser technologies particularly when both the sensor and obstacle are in motion and when obstacles have differing unpredictable surface properties.

Keywords: Obstacle Detection, Driver Profiling, Ultrasound, Ultrasonic Sensors, Bayesian Network, 2TBN, Sensor Fusion, Driver Assistance.

B. In Press (Paper Presented in the IEEE AFRICON 2019 Conference)

Title: A Software Agent for Vehicle Driver Modeling

Abstract: The world is experiencing a paradigm shift towards intelligent agents in form of machine learning for modelling any given task or process. Human vehicle drivers are agents that operate under stochastic environments, full of other agents. Such environments are complex to perceive and model. This study explores how a utility-based agent could be used to model human vehicle drivers. The motivation behind this study was established on the assumption that a driver agent founded on GPS data, Mixture Models and probabilistic reasoning methodologies could effectively model human vehicle driver actions. The significance of the study is four-fold: First, the function of the system could be extended to providing advisory services to drivers in real-time. Second, data gathered from the system could be used by road safety stakeholders to vet drivers and to diagnose causes of road accidents. Thirdly, the resulting knowledge-base could establish standards of rationality in driving and/or formulate rules for use in driverless vehicle control systems. Finally, the model could be used to build a dataset on driver behaviour for any given vehicle driver and type and nature of operational environment.

Keywords: Driver Agent, Driver Model, Driver Behaviour, Probabilistic Reasoning, Mixture Models.

C. Earlier Conferences and Publications in the Same Area

Title: Use of GPS with road mapping for traffic analysis [74]

Abstract: Traffic control and management requires high-tech computerized solutions as opposed to the manual methods that commonly involve the use of traffic policemen, traffic lights and safety cameras. Collection and analysis of road traffic data is a key requirement towards establishment of traffic conditions on any given road segments. This paper explores the use of the Global Positioning System (GPS) technology incorporated with road mapping focused at traffic data collection and analysis of traffic conditions. A GPS data receiver application and traffic analysis system was developed that collects GPS traffic data and provides the ability for monitoring and analyzing traffic scenarios on the roads, for instance the speed of traffic. It also provides planners on the road usage patterns for decision making. All these aspects can be analysed both in real-time and historically basing on the fact that historical data is captured and stored for future use. The system has an addition ability to trigger email alerts on speeding vehicles. The results show that there is great need for real-time traffic information analysis due to the tremendous variability in traffic scenarios in major cities like Nairobi, Kenya. The system has been used to show changes in position, speed and directions of vehicles travelling on the Kenyan roads with the speed of traffic algorithm developed and effectively put in place. The established centralized GPS server database provides a means of various kinds of analysis. Using the geographic components in the collected GPS data, and visualizing by mapping, provides a clearer view of the traffic conditions for any given region. Challenges facing the existing systems could be mitigated through the adoption of the GPS based system.

Keywords: GPS, Traffic Analysis, Road Usage Pattern, Road Mapping, Traffic Speed Analysis

APPENDIX H: RESEARCH SCHEDULE

Table 0.19. Monthly Task Research Schedule

	Year One												Year Two												Year Three											
Task	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M
Develop Research Proposal	■	■	■	■	■	■	■	■	■	■	■	■	■	■																						
Proposal Defense & Revisions														■	■																					
Develop & Setup GPS Server																■	■	■																		
Develop the Driver Agent																■	■	■																		
Sample Target Vehicles Selection																			■																	
Installation of GPS Receivers & Sensors																			■	■																
Training of the Driver Agent																					■	■														
Testing of the Driver Agent																							■	■												
Agent Validation: Process & Analyse Data																									■	■										
Write Thesis Chapters																								■	■	■	■	■								
Submit Thesis - First Full Draft																												■	■							
Revisions of First Full Draft																													■	■	■					
Submission of Revised Version																															■	■				
Defense and Revisions																																	■	■		
Submit Final Thesis Document																																			■	■

APPENDIX I: RESEARCH BUDGET

Table 0.20. Yearly Itemised Research Budget

Item Name	**Year 1**	**Year 2**	**Year 3**
1. Expendable Supplies			
Printer Tonner	5,000	5,000	15,000
Printing Papers	5,000	5,000	10,000
Sub-Total	**10,000**	**10,000**	**25,000**
2. Software Requirements			
GPS Server Application and Agent Development and Improvement	0	150,000	0
SPSS for Analysis	0	50,000	0
Sub-Total	**0**	**200,000**	**0**
3. Hardware Requirements			
GPS Receivers (5 pieces)	0	100,000	0
GSM SIMs (5 pieces)	0	500	0
Proximity sensors (20 pieces)	0	100,000	0
Other Accessories:			
▪ Microcontroller – Arduino Uno (5 pieces)	0	15,000	0
▪ 40 Pin DIP IC Socket (10 pieces)	0	1,000	0
▪ LCD 1602 Display – yellow (4 pieces)	0	2,000	0
▪ LCD 1602 Serial Adapter (10 pieces)	0	4,000	0
▪ Power supplies (5 pieces)	0	5,000	0
▪ Tapes with Rubber Adhesive; Data Cables; Capacitors; Resistors; LEDs, Jumper wires (male to female)	0	30,000	0
Sub-Total	**0**	**257,500**	**0**
4. Documentation and Publication Costs			
4 Publications	5,000	5,000	10,000
4 Project Seminars	5,000	5,000	10,000
4 Conferences	5,000	5,000	10,000
Sub-total	**15,000**	**15,000**	**30,000**
5. Traveling Costs			
Local traveling while collecting data	10,000	20,000	20,000
Sub-Total	**10,000**	**20,000**	**20,000**
6. Extra Personnel			
4 Research assistants	0	80,000	80,000
2 Application developers	0	100,000	0
Sub-Total	**0**	**180,000**	**80,000**
7. Other Costs			
GPS Receiver Installation (Man Power)	0	40,000	0
Mobile data	0	15,000	0
Internet Connectivity to the GPS Server	0	20,000	10,000
Sub-Total	**0**	**75,000**	**10,000**
Total Yearly budget	**35,000**	**757,500**	**165,000**
8. Miscellaneous			
Miscellaneous (10% of Total Cost)	3,500	75,750	16,500
Grand Yearly Total	**38,500**	**833,250**	**181,500**
GRAND TOTAL			**1,053,250**
TOTAL BUDGET: One million fifty three thousand, two hundred and fifty only			

APPENDIX J: RESEARCH APPROVAL AND PERMIT

MASENO UNIVERSITY
SCHOOL OF GRADUATE STUDIES

Office of the Dean

Our Ref: PHD/CI/00054/2014

Private Bag, MASENO, KENYA
Tel:(057)351 22/351008/351011
FAX: 254-057-351153/351221
Email: sgs@maseno.ac.ke

Date: 20th DEC, 2017

TO WHOM IT MAY CONCERN

RE: PROPOSAL APPROVAL FOR JAMES OBUHUMA IMENDE— PHD/CI/00054/2014

The above named is registered in the Doctor of Philosophy Programme in the School Computing and informatics, Maseno University. This is to confirm that his research proposal titled **"A utility-based agent for vehicle driver moldeling"** has been approved for conduct of research subject to obtaining all other permissions/clearances that may be required beforehand.

Prof. J. O. Agure
DEAN, SCHOOL OF GRADUATE STUDIES

Maseno University *ISO 9001:2008 Certified*

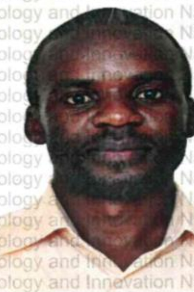
Figure 0.2. Study Approval Letter by School of Graduate Studies, Maseno University

THIS IS TO CERTIFY THAT:
MR. JAMES OBUHUMA IMENDE
of MASENO UNIVERSITY, 0-200
Nairobi,has been permitted to conduct
research in *All Counties*

on the topic: *A UTILITY-BASED AGENT FOR VEHICLE DRIVER MODELING*

for the period ending:
9th October,2019

Permit No : NACOSTI/P/18/82147/25504
Date Of Issue : 9th October,2018
Fee Recieved :Ksh 2000



....
Applicant's Signature

....
Director General
National Commission for Science, Technology & Innovation

Figure 0.3. Research Permit (NACOSTI)