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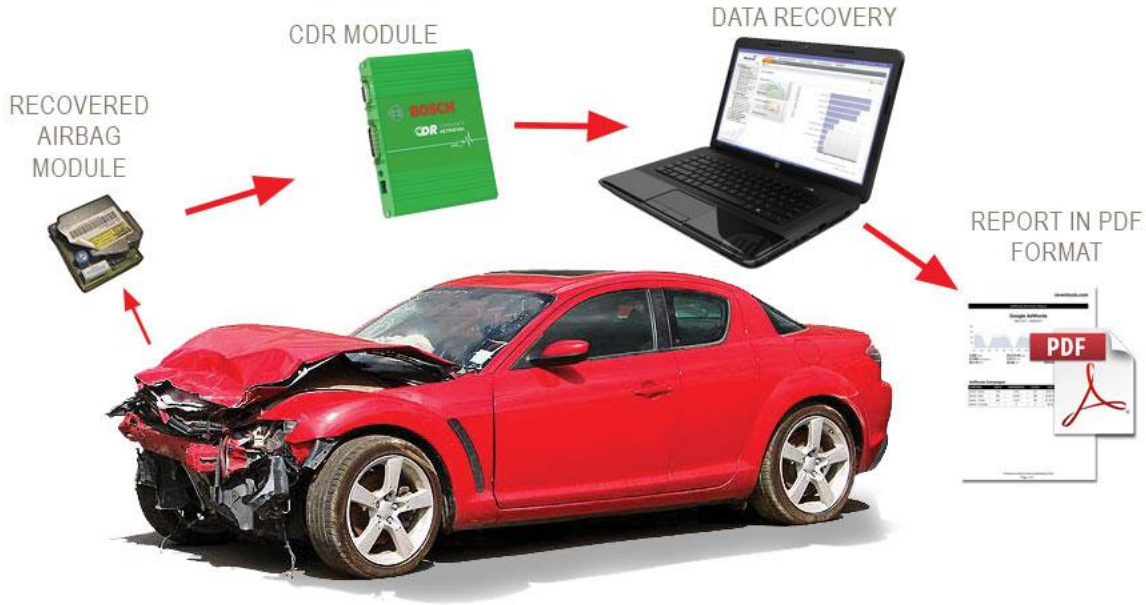

Using Event Data Recorder (EDR) data to perform What-if simulations for safety benefit analysis by reconstructing real traffic kinematics and driver behaviors

Master's thesis in Mechanical Engineering

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CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2017

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Abstract

As the focus of traffic safety stakeholders shifts from passive safety to active safety, the need to predictively evaluate safety systems in addition to identifying driver behaviour in critical situations has come to the forefront. Availability of a wide variety of data has opened up new research possibilities; real world crash data is increasingly accessible through Event Data Recorder (EDR) data, although little information is available about the context of the crash. Naturalistic Driving Data (NDD) addresses this issue by monitoring the driver and vehicle with the help of cameras and sensors. However, there is a lack of real world crashes associated with NDD. Therefore, the need to combine data sources to identify driver behaviour and estimate safety benefit has never been higher. In this study Counterfactual or 'What-if' simulations are performed with EDR data of real rear-end crashes and driver glance behaviours inspired from NDD to assess the impact of different driver glance behaviour on possible outcomes. The data was extracted from the National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) database for use in the What-if simulations. Artificial kinematics or Counter factual kinematics was created by removing the evasive (braking) manoeuver. A glance anchor point (AP) based on literature was chosen. Two distributions (Baseline glance distribution, Reaction time distribution) and a deceleration value were applied to the kinematics at the AP. The Baseline Glance distribution which represented normal everyday driving was inspired from NDD. The reaction time distribution and deceleration value was created and chosen based on literature respectively. The application of the combination of distributions resulted in counter factual outcomes with two possibilities: Crash or No Crash. The Impact speeds of all the counter factual events that resulted in a Crash were calculated. Another batch of simulations was performed replacing the Baseline Glance distribution with the Rockwell glance distribution. The Rockwell glance distribution represented the glance durations associated with a well-known secondary task of tuning a radio. Results were compared between outcomes from Baseline Glance Distribution and Rockwell Glance distribution with the Original crash data as reference. The results showed that the Baseline Glance distribution had lower percentage of crashes when compared to the Rockwell glance distribution. The impact speeds associated with the Rockwell glance distribution were much higher than the Baseline. However, the impact speeds resulting from both distributions were much lower compared to the impact speeds associated with the original crashes which clearly indicated the high severity of the original crashes. The methodology and results from this study provide the necessary framework to evaluate the benefit of rear end collision avoidance safety systems. Also, a basis for understanding driver behaviour prior to critical situations is provided.

Keywords: Event Data Recorder (EDR), Driver glance behaviour, Counterfactual simulations, Rear end collision, Safety benefit, Active Safety System evaluation

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Rakshith Mukunda Rao
Göteborg, 2017

List of Abbreviations

ABS	Anti-lock Braking System
ADAS	Advanced Driver Assistance System
ACN	Automatic Crash Notification
AEB	Autonomous Emergency Brake
AIS	Abbreviated Injury Scale
ANDS	Australian Naturalistic Driving Study
ANNEXT	Analysis of Naturalistic External Datasets
AP	Anchor Point
C	Crash
CDR	Crash Data Recovery
CFR	Code of Federal Regulation
CIREN	Crash Injury Research and Engineering Network
CISS	Crash Investigation Sampling System
EDR	Event Data Recorder
ELG	End of Last Glance off road
EM	Evasive Manoeuver
EOFF	Eyes Off road
EON	Eyes On road
FCW	Forward Collision Warning
ftp	file transfer protocol
GES	General Estimate System
GM	General Motors
GPS	Global Positioning System
LV	Lead Vehicle
LVD	Lead Vehicle Decelerating
LVM	Lead Vehicle Moving
LVS	Lead Vehicle Stopped
MAIS3+	Maximum Abbreviated Injury Scale
MCR	Model estimated Crash Risk
MIR	Model estimated Injury Risk
NASS-CDS	National Automotive Sampling System - Crashworthiness Data System
NC	No Crash
NDD	Naturalistic Driving Data
NDS	Naturalistic Driving Study
NHTSA	National Highway Traffic Safety Administration
OEM	Original Equipment Manufacturer
PSU	Primary Sampling Unit
R&D	Research and Development
SAS	Statistical Analysis System
SCI	Special Crash Investigation
SHRP2	Second Strategic Highway Research Programme
SPSS	Statistical Package for Social Sciences
SUV	Sports Utility Vehicle
SV	Subject Vehicle
TASA	Technical Advisory Service for Attorneys
TTC	Time To Collision
UDRIVE	European naturalistic Driving and Riding for Infrastructure & Vehicle Safety and Environment
US-DoT	United States – Department of Transportation
USA	United States of America

List of Notations

m	metre
s	second

rad	radian
m/s	metre per second
m/s^2	metre per second squared
rad/s	radian per second
km/h	kilometre per hour
g	Acceleration due to gravity (= 9.81) [m/s^2]
theta (θ)	Optical angle [rad]
thetadot ($\dot{\theta}$)	Optical expansion rate or Looming [rad/s]
τ^{-1}	Inverse Tau (= $\dot{\theta}$ / θ)[s^{-1}]
TTC^{-1}	Inverse TTC [s^{-1}]
V1	Vehicle one
V2	Vehicle two

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1 Introduction

In the last decade, focus of automotive safety stakeholders has been more on preventing crashes rather than lessening severity, i.e. majority of the attention has shifted to active safety from passive safety although a steady focus on passive safety is being maintained (Schoeneburg & Breitling, 2005). Advanced Driver Assistance Systems (ADAS) are undergoing improvement as knowledge of the relationships between vehicle and environments continue to grow. Another contributing factor is the rapid growth of sensor technologies. For effective active safety ADAS evaluation, knowledge of vehicle and driver behaviour prior to a crash is vital. Although knowledge of vehicle behaviour is available, understanding driver behaviour seems to be the Achilles heel. Vast amount of research has been undergoing for decades and only recently driver behaviour quantification has taken centre stage (Benderius & Markkula, 2015; VINNOVA, 2016).

Previous research governing safety system evaluation and driver behaviour have been largely based on test track experiments and simulator studies (Kiefer, Salinger, & Ference, 2005) but of late, access to real world crash data seems to be increasing. The availability of Event Data Recorder (EDR) data opened up vast possibilities of research. More importantly, information of driver behaviour prior to the crash is available which could be crucial for safety system design and evaluation. Kusano and Gabler (2011) leverage this information to estimate variables critical for rear end collision safety system design highlighting its potential. Also, driver acceptance to safety systems can be evaluated to an extent based on tendencies prior to a crash. Although, EDR data gives pre-crash, crash and post-crash information, little is known about the context of the situation leading to the crash. Naturalistic Driving Studies (NDS) fill this gap with detailed monitoring of the driver and vehicle with the help of cameras and sensors. Driving patterns, glances off road, involvement in secondary tasks (radio, texting, calling, adjusting mirrors), driver inattention due to drowsiness are some of the information that are available. As informative as it may be, there is however a lack of real world crash data associated with these studies (Bärgman, Lisovskaja, Victor, Flannagan, & Dozza, 2015). It is therefore indispensable that data sources are combined with one another in ways that complement each other.

Counter factual simulations are one way of using Naturalistic Driving Data (NDD) to estimate safety benefit of safety systems and observe the effect of glance behaviour on outcomes. These simulations provide a platform for predictive evaluation of active safety systems. To address the problem of context dependence in crashes and near crashes, studies on glance behaviour using Naturalistic Driving Data have been carried out by Bärgman et al. (2015) in which they estimate risk of crash and injury through 'What-if' or counterfactual simulations. Also, in another study, Bärgman, Boda, and Dozza (2016) used counterfactual simulations to estimate the benefit of safety systems using different driver behaviour models using specific glance behaviours.

The current study addresses the need to combine data sources by using real world crash data and driver glance behaviours (inspired from NDS) to perform What-if simulations to assess the impact of driver glance behaviour on crashes; a methodology which addresses one of the research gaps in the work of Bärgman et al. (2016). The main objective is to present a methodology framework using Event Data Recorder (EDR) data of rear end collisions to perform 'What-if' or Counter-factual simulations to observe the effect of different driver glance behaviours on possible outcomes (Crash or No crash) and Impact speeds. This study establishes a sound framework which would pave the way forward for ADAS designers to refine, evaluate and estimate safety benefit of Active Safety Systems. Also, this study hopes to aid researchers trying to ascertain driver behaviour prior to a collision.

2 Literature review

2.1 Naturalistic Driving Studies (NDS)

In the context of driving and traffic safety, the word ‘naturalistic’ means unobtrusive observation (Dingus et al., 2006). Naturalistic Driving Studies (NDS) have been carried out to ascertain driver behaviour and driving styles in normal everyday situations and safety critical situations. NDS is defined as “A study undertaken to provide insight into driver behaviour during everyday trips by recording details of the driver, the vehicle and surroundings through unobtrusive data gathering equipment and without experimental control” (Van Schagen et al., 2011, p-6). NDS were employed to address gaps in empirical data collection (test tracks and simulators) and epidemiological data collection (crash databases). The main gaps in empirical data were that the test subjects would often modify their driver behaviour just because of the experimental setting and the fact that they would know they would not be harmed in case an incident occurred because it was just a simulator study. Crash databases suggest that driver inattention was usually the cause of crashes but this information would be based on the reports of police and eyewitnesses (Dingus et al., 2006). The main advantage of NDS compared to other types of studies is that, in NDS, subjects behave spontaneously.

There are many NDS that have been carried out and some currently being carried out. Some of the programs are 100-car study (USA), Second Strategic Highway Research Program (SHRP2, USA), eUropean Naturalistic Driving and Riding for Infrastructure and Vehicle safety and Environment (UDRIVE, Europe) and Australian Naturalistic Driving Study (ANDS, Australia). The 100-car study was the first NDS to be undertaken on 100 instrumented cars (Dingus et al., 2006). Dingus et al. (2006) primarily wanted to address the impact of driver inattention on crash and near crash risk and how often driver inattention would occur on a normal roadway environment. Through unobtrusive monitoring, NDD includes information regarding the driver, vehicle and environment (also other road users). The data is collected through sensors, cameras, and Global Positioning System (GPS). Another comprehensively large NDS called the SHRP2 NDS (2005 – 2015) aimed to provide a comprehensive dataset to decipher driver behaviour, driver performance, driver-vehicle interactions, and driver-environment interaction (Victor et al., 2015).

2.2 Event Data Recorder (EDR)

“An EDR can be defined as device or function in a vehicle that records a vehicle’s dynamic, time-series data just prior to or during a crash, intended for retrieval after the crash” (NHTSA, 2006b, p1). Typically the EDR captures data when there is an airbag deployment event (although some EDRs also capture data after a non-deployment event). If captured, pre-crash EDR data will be crucial in deducing driver behaviour just before an occurrence of a crash.

EDR data became accessible to the public from the year 2000 although the data is not standardized due to vehicle manufacturer’s contrasting views on the subject of data collection devices and its access (NHTSA, 2006a). The availability of quality EDR data (high percentage of pre-crash data) has been increasing over the years (2012 onwards) courtesy of National Highway Traffic Safety Administration (NHTSA) who proposed a series of rule and policy changes so that the acquisition of data during the crash and retrieval of data after the crash are standardized to an extent (NHTSA, 2006a).

NHTSA's (2006a) federal document ‘49 CFR (Code for Federal Regulation), Part 563’ gives the Final rule for EDRs. The final rule is a requirements document that specifies the accuracy, storage, collection, retrievability and survivability of EDRs for vehicles that are involved in crashes that are fitted with EDRs. The final rule hopes to ensure standardization for later use so that emergency care can be accelerated. This standardization is expected to ensure efficient procedures for Automatic Crash Notifications (ACN) and Crash data retrieval. It also claims that analysis of EDR data can lead to safer vehicle designs and proper understanding of the causation mechanisms and the circumstances leading to it. The final rule makes an effort to regulate voluntarily provided EDRs to provide a set of data elements that should have standard range, accuracy and resolution requirements.

Care should be taken while dealing with EDR data as there are limitations like different sampling rates- pre-crash and crash variables, non-uniformity in synchronization of crash timing etc. (see Section 6.2.1). A webinar hosted by the Technical Advisory Service for Attorneys (TASA) can be viewed to get an overview of the role of EDRs in accident reconstruction (TASA Group & George H. Meinschein, n.d.).

2.3 Comparison between NDS and EDR data

NDS give access to contextual information in a driving setting. (For example, the actions of the driver, the kinematic information of the instrumented vehicle, actions of other road users (other vehicles, bicyclists, pedestrians), environmental conditions (weather, road conditions, traffic infrastructure) and a variety of information. Consequently, the situation leading to crashes and near crashes can be analysed objectively and subjectively. Drivers' braking and steering behaviours can be deduced, glance behaviours in different traffic/roadway situations can be observed, interaction of driver and in-vehicle system interfaces can be seen; all at the same time with access to information like vehicle speed, status of safety systems (if present), position of vehicle on the road and other information. With the amount of data available from different NDS as mentioned in Section 2.1, one would ask the question "Why is any other kind of data source even required?" The answer to that question is fairly simple: There is a lack of Crash data associated with NDD (Bärgman et al., 2016, 2015) and therefore near crashes are used as 'substitutes' for crashes. There is a widespread debate about the usage of near crashes instead of crashes in the research community which Bärgman (2016) discusses about at length. As the debate rages on, alternate sources of real crash data like EDR data have been increasingly available.

EDR data gives information about the seconds leading up to a crash (if available), during the crash and after the crash. This pre-crash information can be vital to assess drivers' braking behaviours (in some cases, steering behaviour) prior to a crash. The pre-crash information generally includes time series information, vehicle speed, and brake status. In addition to these variables, some advanced EDRs record engine speed, throttle percentage, steering angle, yaw rate, safety system status and other information. Researchers can calculate the evasive patterns (braking and steering), magnitude of evasive manoeuvres (deceleration and yaw rate), frequency of evasive manoeuvres, Time to collision and other metrics critical for ADAS design and evaluation (Kusano & Gabler, 2011; Scanlon, Kusano, & Gabler, 2015; Scanlon, Page, Sherony, & Gabler, 2016). Although EDR data gives detailed pre-crash information, it does not provide contextual information. Naturally the question arises "How can EDR data be used in other ways to determine the cause of the crash?" The answer is to combine data sources in ways that complement each other which Bärgman et al. (2016) proposed as future work. This thesis study addresses this research gap by using rear end crash data obtained from EDRs and glance behaviours extracted from NDD. In doing so, the original crash signature is retained whilst also incorporating probable context-dependent behaviours.

2.4 Rear end collisions

A rear end collision is a type of crash configuration where the front of one vehicle (Subject Vehicle (SV)) impacts the rear of another vehicle travelling in the same direction (Lead Vehicle (LV)). According to Lee, Llaneras, Klauer, and Sudweeks (2007), rear end crashes are the most frequent type of crashes that occur which account for 29% of the all crashes resulting in a number injuries and fatalities. Rear end scenario was chosen in this study as it was relatively simple to model as only longitudinal kinematics needed to be considered. Another contributing factor in choosing rear end scenarios was because rear end scenarios had the highest societal cost (Najm et al., 2013). NHTSA specifies mainly three rear end configurations; they are Lead Vehicle Stopped (LVS), Lead Vehicle Decelerating (LVD) and Lead Vehicle Moving (LVM). LVS scenarios will be considered in this study. In LVS scenarios, the LV is at a standstill when the crash occurs, in LVD scenarios the LV is decelerating to a stop before or at the occurrence of the crash and in LVM scenarios, the LV is moving at a constant slow speed. The subsections of these categories can be seen in Figure 3.3.

The central aspects of driver behaviour that have to be addressed almost as an obligation when considering rear end scenarios are reaction times and braking (deceleration) levels. Emphasis will be on reaction times in this section. There are various definitions of reaction times present in literature. According to a web article written by Neilsen (n.d.), there are 4 components related to stopping distance which are Human Perception time, Human Reaction time, Vehicle Reaction time and Vehicle Braking Capability. The first two components are human factors and the last two components are vehicle factors responsible for braking. The Human perception time is the time taken by the human brain to see a hazard, and recognize it as a hazard for which action should have to be taken. The time taken by the driver after recognizing the hazard to move his/her feet from the accelerator pedal to the brake pedal and apply pressure on the pedal is called the human reaction time. Once the brakes are applied, the stopping distance depends on the vehicle's capability to brake (Vehicle reaction time – brake actuator delay, Vehicle braking capability – type of brakes, brake pad material etc.). Driver or human reaction time is considered as the sum of the perception time and the time required in moving the foot from the accelerator pedal to the brake pedal (Gerlough & Huber, 1975). The delay introduced by the vehicle (brake system actuation delay) is generally not considered in microscopic traffic simulation models (Ma & Andréasson, 2006).

Green (2000) states in his work that the definition of reaction time used in literature is inconsistent and he defines the reaction time to be the sum of the perception time and foot movement time. He makes distinctions of reaction time with respect to expected, unexpected and surprise situations. From his findings he claims that that reaction times for expected, unexpected and surprise situations are 0.7 s, 1.25 s and 1.5 s respectively and states that these values can change based on age, gender, fatigue, cognitive load and urgency/criticality. Summala (2000) states in his commentary of Green's (2000) article on reaction times that urgency/criticality of the situation in fact, plays a very important role in determining reaction times in addition to expectancies (or the lack of it). Summala (2000) along with other researchers believed that driving is not only about response to emergency situations or pre-defined stimuli with a standard reaction time, but it is the continuous modulation of safety margins as per the situation and this depends on factors such as driving experience and situational awareness. In a recent study, Markkula, Engström, Lodin, Bärgman, and Victor (2016) justify that reaction times are primarily dependent on the urgency/criticality of the situation and state that reaction times could be much lower for unexpected or surprise situations in contrast to Green's (2000) stand on reaction times during unexpected and surprise situations.

2.5 Counterfactual Simulations

This section will describe the current state of the art on counterfactual simulations as it is relevant in this study. Counterfactual simulations describe a set of possible outcomes based on different combinations of inputs using different mathematical models (Driver models, vehicle models, environment models, algorithms of safety systems etc.). Kusano and Gabler (2012) use EDR data and present a methodology mainly consisting of mathematical simulations using algorithms of safety systems to assess the effectiveness of safety systems by observing the percentage of impact speeds reduced and injuries prevented. The results of their simulations were compared to results obtained without the usage of safety system algorithms. McLaughlin, Hankey, and Dingus (2008) use data from NDS to evaluate collision avoidance systems by using NDD as inputs to collision alert models to determine the triggering point of the alerts, time available before a collision after the alert and the frequency of the alerts generated. The point to be noted in their research was that they used data from crashes and near crashes and did not evaluate the collision avoidance systems based on specific reaction times but on reaction time distributions from previous literature.

The counterfactual simulation involving glance behaviour in the current study was inspired by the works of Bärgman et al. (2015). Lacking a method to observe the influence of driver glance behaviour on the risk of crashes and injuries, counterfactual simulations using crash and near crash data from NDS were run to explore further the relationship between glance behaviour and crash and injury risk (Bärgman et al., 2015). 'What-if' or counterfactual simulations aim to deduce what might have happened in a crash (before and during) if the driver had exhibited a different kind of behaviour. Bärgman et al. (2015) use video data of glance behaviour of normal everyday driving (called the baseline glance distribution) from SHRP2 dataset for the simulations and since off road glance behaviour can represent other secondary tasks such as tuning the radio, texting on the cell-phone etc. they use the Rockwell glance distribution arising from a standard secondary task of tuning a radio (Rockwell, 1988) in their analysis. Two other hypothetical distributions were created based on the existing Rockwell distribution so that the effect could be generalized. When they analysed the dataset, they removed the actual glances of the drivers and applied these distributions to calculate probabilities. A range of variables like Time To Collision (TTC), TTC^{-1}, deceleration rates, severity based on impact speeds and injury (Abbreviated Injury Scale (AIS)) were used as information to conduct the simulations. They create severity metrics like Model estimated Injury Risk (MIR) and Model estimated Crash Risk (MCR) based on injury scales like the MAIS3+ (Maximum Abbreviated Scale of Injury). They define these indices (MIR and MCR) to be expected risk of injury and probability of a safety critical event becoming a crash. They also define an anchor point based on the work of Victor et al. (2015) and run the simulations. They find that the having eyes on road and reducing long glances by performing the tasks faster result in lower crash and injury risk. They also propose that the MCR and MIR can be used in the evaluation of ADAS.

In a later study performed (Bärgman et al., 2016), counterfactual simulations were performed using pre-crash kinematic data only from real crashes from the SHRP2 NDS to estimate the safety benefit of FCW, AEB and FCW+AEB together. They demonstrate the importance of choosing different driver models (driver glance model, driver reaction model and driver braking model) on the safety benefit of the aforementioned ADAS. Their results showed that the choosing of the driver model had a considerable impact on the evaluation of ADAS. They also state that the characteristics of the glance distributions have some impact, but more importantly, the placement of glances sampled from a distribution with respect to an 'Anchor Point (AP)' in the pre-crash phase of the counterfactual simulations plays a critical role in the benefit analysis of ADAS especially the ADAS which include the driver in the loop. The reason they make the comment that the glance distribution is less important than the anchor point is because a.) The type of glances (short, mid, long) exhibited by the driver before the anchor point is irrelevant on the possible/probable outcomes and b.) It is the tail of the glance distribution that matters for most pre-crash kinematics and as long as the tails of the distributions have a similar shape between two distributions (example: exponential), the counterfactual outcome will be similar for the same pre-crash kinematics.

3 Data extraction and usage

Since this study aims to concentrate on actions before the collision, the focus will only be on pre-crash kinematics (Vehicle speed time series data and its derivative) and this study will focus on the 'stationary rear end crash (as per NASS CDS, Lead Vehicle Stopped (LVS))' type of data. This section will present a brief background of EDR retrieval, a small section on Crash Data Retrieval System and finally a section on the NASS CDS database and the way of narrowing down the data with the required variables of interest.

3.1 Background of EDR data retrieval

EDR data was collected by the National Highway Traffic Safety Administration (NHTSA) of the United States Department of Transportation (US-DoT) since the 1990s. During these primitive stages of EDR data collection, it was NHTSA's Special Crash Investigation (SCI) teams that were given the responsibility of data collection and analysis during investigation of crashes (NHTSA, 2001). Since Original Equipment Manufacturers (OEMs) did not offer the possibility of EDR data retrieval for the public, General Motors (GM) tied up with a company named Vetronix Corporation who developed a tool named 'Crash Data Retrieval (CDR) system' so that data from the EDR could be downloaded and made available to the public. Since the year 2000, NHTSA enabled a few other databases like Crash Injury Research and Engineering Network (CIREN), and National Automotive Sampling System – Crashworthiness Data System (NASS-CDS) to collect and analyze EDR data (Mynatt, Brophy, & Chidester, 2015; NHTSA, 2001).

As far as the ownership of EDR data is concerned, there are contrasting views stated by different parties (NHTSA, Federal Highway Administration-USA, Insurance companies and Legal experts) as per NHTSA (2001). Only NHTSA's stance (*EDR data belongs to the owner of the vehicle and if governmental agencies and researchers require this data, any type of personal information pertaining to this data would have to be held confidential as per the privacy act*) will be considered as NHTSA is the agency responsible for making the EDR reports 'public'. (For more information, see NHTSA (2006c)). The customers of EDR data as per NHTSA (2001) are divided into 5 categories:

1. R&D – OEMs, Governments, Academics
2. Incident management – Law enforcement, On-Scene crash investigators, Medical, Insurance companies
3. Fault assignment – Authorities (police, court), OEM and Government, Insurance companies through claims etc.
4. Driver – Personal data, Vehicle performance
5. Owner – Fleet, Personal, Self-insured

The future of EDR data collection looks promising as there are steps being taken to standardize the data collected in EDRs (Mynatt et al., 2015; NHTSA, 2001, 2006a). Mynatt et al. (2015) state that there are plans of modernizing the whole EDR data collection database and it would be called Crash Investigation Sampling System (CISS) from January 2016 which would be built upon the existing infrastructure of the NASS CDS.

3.2 Crash Data Retrieval (CDR) system

The Crash Data Retrieval (CDR) system is a tool developed by Vetronix Corporation in the year 2000 so that EDR data can be downloaded by the users from the EDRs installed on passenger and light duty vehicles. Initially, Vetronix had agreements with GM and Ford with respect to EDR data retrieval. In the year 2003, the Vetronix was acquired by Robert Bosch GmbH ("Bosch Diagnostics," n.d., "Vetronix Corporation - Diagnostics and Telematics Solutions," n.d.). After the passing of the final rule (49 CFR, part 563) (see Section 2.2), the standardization of EDR data encouraged different European and Japanese manufacturers to partner up with Bosch and make the data retrievable using the CDR tool.

A software application specified by Bosch has to be downloaded to open the .CDR files. Every year Bosch releases a list of vehicle manufacturers that it covers in its release (Bosch diagnostics CDR software web link). These .CDR files can in no way be tampered with as it contains the raw data of the crash. Once the CDR software is downloaded, the data can be accessed and converted into a .PDF file or a .CSV file. Gaining access in the form of a .CSV files requires the software to be purchased for a fee, whereas the .PDF file can be obtained at no cost.

The data used in this thesis study was only available as .PDF or .CDR files. The NASS CDS file transfer protocol (ftp) database contains these .CDR or .PDF files in addition to various other details (Statistical Analysis Software (SAS) database files) of the crash (Vehicle, occupant, and environment). A description of the NASS CDS database with focus on downloaded EDR data used in this thesis report is presented in Section 3.3.

3.3 NASS CDS database and 'narrowing down' of available EDR data

The National Automotive Sampling System (NASS) is a nationally representative database which provides NHTSA with resources to conduct crash data collection. NASS consists of two parts: the Crashworthiness Data System (CDS) and the General Estimates System (GES). The CDS helps to improve vehicle design by investigating injury mechanisms and driving behaviour with focus on passenger vehicle crashes. The GES on the other hand is used for trend analyses and identification of the size of problem by focusing on the bigger picture of the crash. Focus will only be on the CDS; the GES is not in the scope of this thesis.

The NASS CDS contains data on random and representative samples of fatal, serious and minor crashes. 4000-5000 crashes involving passenger cars and light duty vehicles are studied by field researchers stationed at Primary Sampling Units (PSUs) every year (PSUs consist of cities, counties or groups of counties divided across 4 regions across the USA). Trained experts, forensic analysts, and crash investigators study on scene evidence such as broken glass, skid marks and impacted guard rails. Also, they locate the vehicle(s) of interest and measure deformations, inspect interior intrusions, take pictures and assess impact damage. Crash Severity is measured based on energy calculations of change in velocity (Delta-V). EDR data is also collected when available. Finally, interviews are conducted on the victims of the crash and their medical records are reviewed to gauge injury severity. These interviews are confidential and discreet and any kind of personal information that can identify the victims is not included in the NASS database. One of the criteria for a crash to be included in the NASS CDS database was that one of the vehicles involved in the crash had to be towed away which is an indication of the high severity of the crash. The NASS CDS has two sources from where data can be viewed and downloaded. The NASS CDS Case viewer ("NASS CDS Case viewer," n.d.) and the NASS CDS file transfer protocol (ftp) ("NASS CDS ftp," n.d.) server. These data sources used in conjunction with each other can narrow down data of interest to a good extent.

The case viewer can be used to gain an overview of the crash. There are many ways in which the required crash of interest can be found on the case viewer. To view a specific case, the year, PSU and the crash number are entered directly to get the required case details. A list of cases fulfilling various other search criteria can also be obtained. Figure 3.1 shows the screenshot of the Case viewer form. The case viewer hosts a mix of subjective and objective information when details of a single case are sought. Figure 3.2 shows the screenshot of the case viewer showing an assortment of information pertaining to an example case named *'Case 2014-04-016'*. In addition to pictures from the crash including the vehicles, skid marks, and guard rails, sketches of vehicles and reconstruction diagrams are also available. A brief summary of the crash is described to better comprehend the context of the crash.

The ftp server on the other hand contains a detailed list of files ranging from database files, text files, change logs, and EDR reports (.PDF or .CDR). The EDR reports in the ftp server are of primary importance, but the caveat is that the EDR reports are classified only based on the year of crash. This implied that the contents consisted of all crashes in which there were EDRs involved. Through some understanding of the coding scheme used in the database files, the type of crash could be ascertained (Radja, 2015). There are various types of crashes that occur in everyday driving situations as shown in Table 3.1. It gives an overview of the crash categories and classifications stated in the Coding manual authored by Radja (2015).

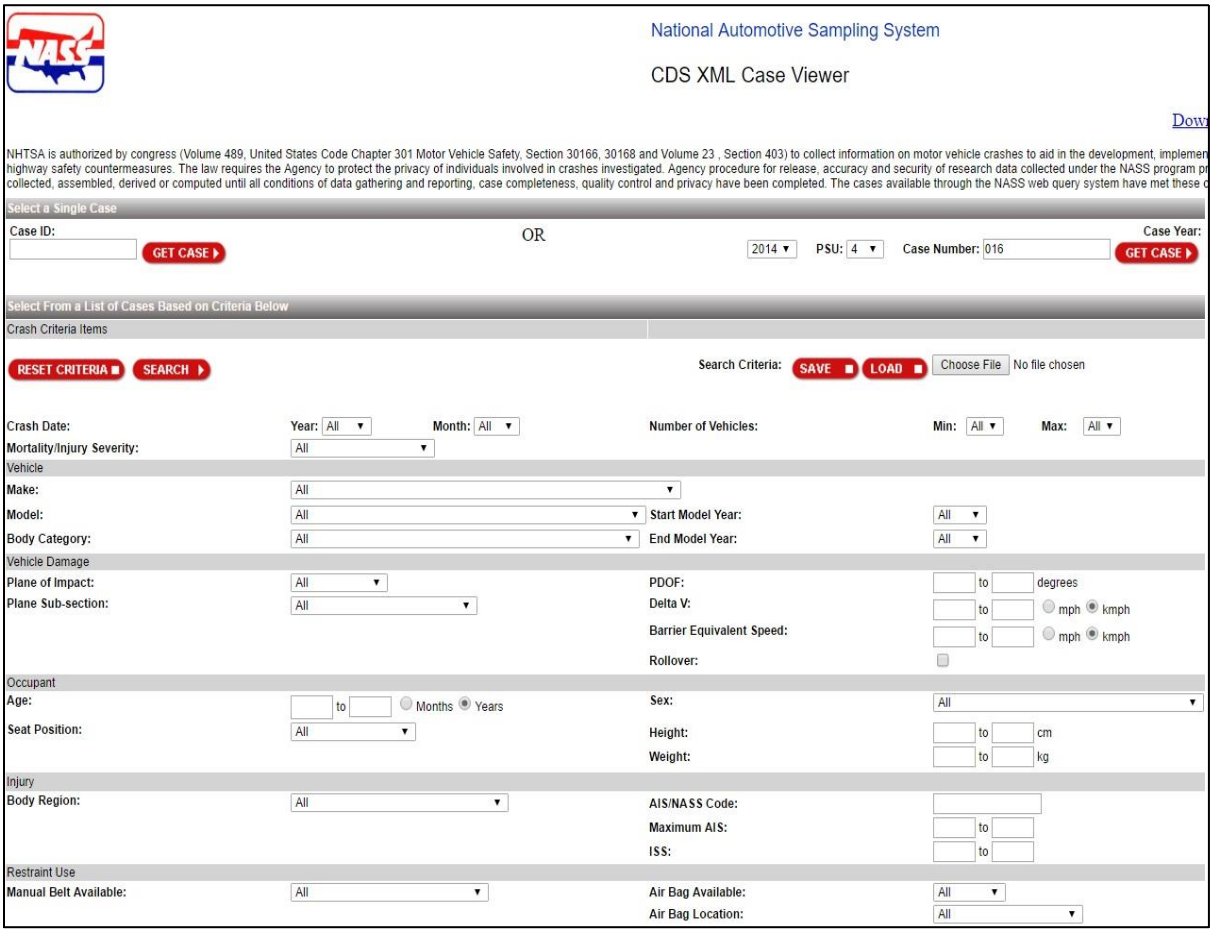

Figure 3.1: NASS CDS Case Viewer

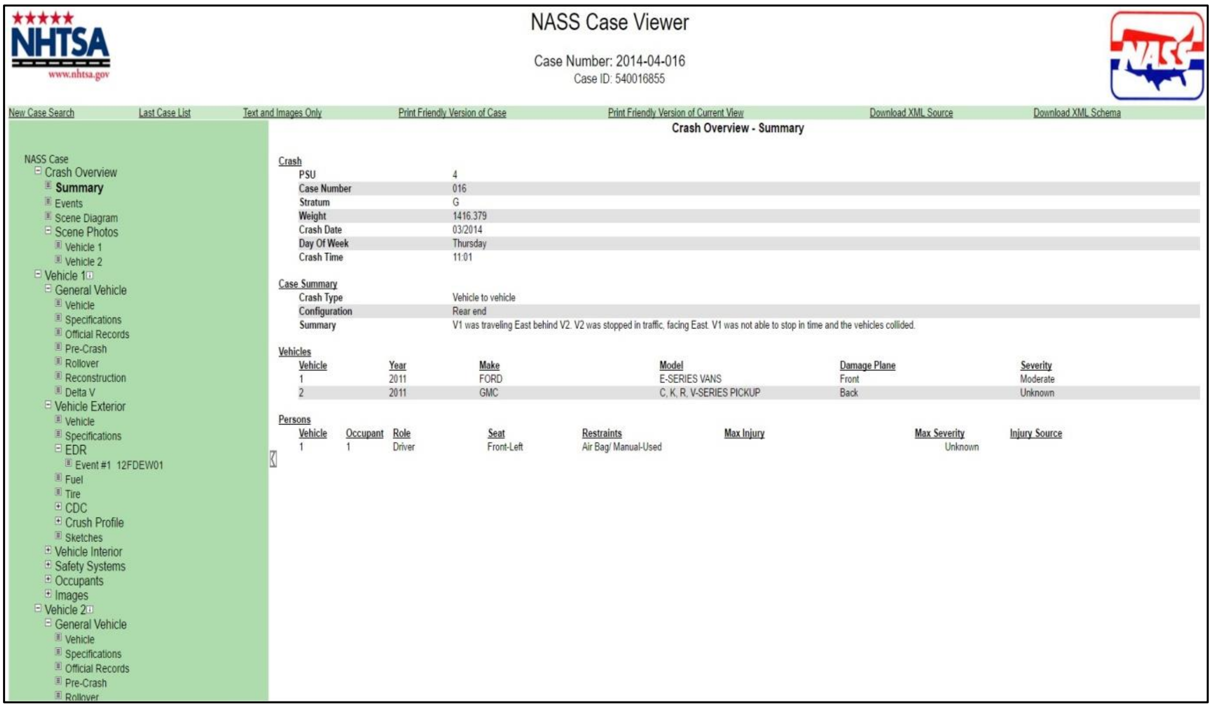

Figure 3.2: Details of Case 2014-04-016 from NASS CDS Case Viewer

Table 3.1: Categories and Classifications of Crashes according to Coding manual (NHTSA)

Crash Category	Crash Classification
Single Driver	Right Roadside Departure
	Left Roadside Departure
	Forward Impact
Same Trafficway, Same Direction	Rear-End
	Forward Impact
	Sideswipe/Angle
Same Trafficway, Opposite Direction	Head-on
	Forward Impact
	Sideswipe/Angle
Change Trafficway Vehicle Turning	Turn Across Path
	Turn Into Path
Intersecting Paths (Vehicle Damage)	Straight Paths
Miscellaneous	Backing, Etc.

Since the core of this study was concentrated on stationary rear-end crashes, further classifications of rear-end crashes is presented in Figure 3.3 so that context of rear-end scenarios could be realized. The oval highlighted in Figure 3.3 showcases the area of interest. ‘Stopped’ is synonymous with ‘Stationary’ and the vehicle in question is the Lead Vehicle (LV).

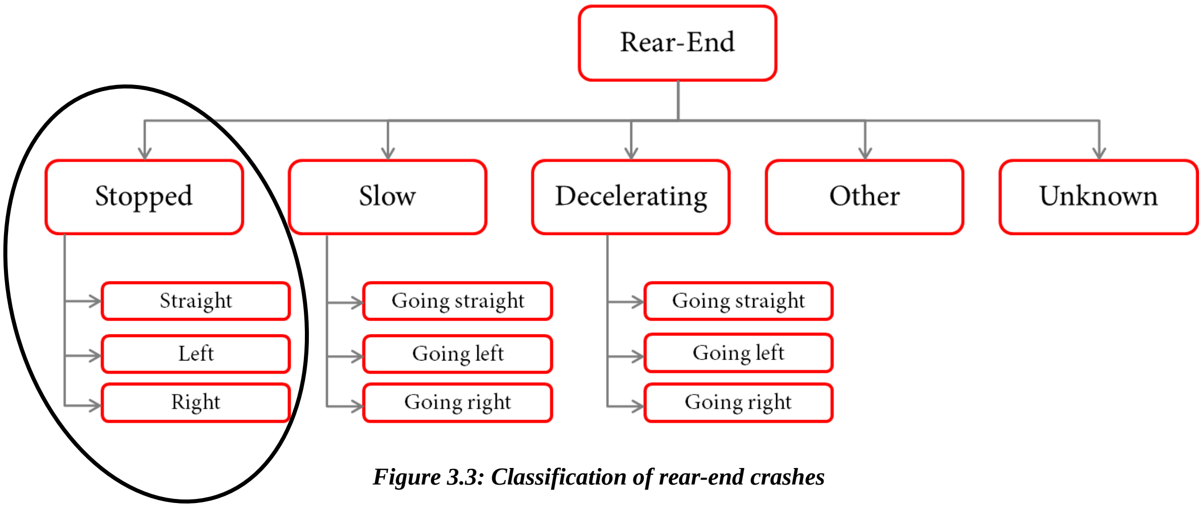

Figure 3.3: Classification of rear-end crashes

Note: The vehicle whose plane of impact is at the front is referred to as Subject Vehicle (SV) and the vehicle whose plane of impact is at the rear is called the Lead Vehicle (LV).

After narrowing down the crash category and classification based on Table 3.1 and Figure 3.3, downloading the required data was the next step. All EDR reports of the year 2014 were downloaded (EDR reports from the year 2014 were chosen as they had the highest percentage of EDR data that contained pre-crash information). The database file named *GV.sasb7dat* was downloaded in order to check which EDR report belonged to a LVS rear end classification. A variable named *ACCTYPE* contained different coding numbers for different classifications (see Figure 3.4). Similar to the highlighting convention used earlier, the black oval in Figure 3.4 shows the rear-end crash of interest with their respective codes. A query was run in Statistical Package for Social Sciences (SPSS) software to give the rear end crash number and PSU. Automated file matching and extraction was done with the help of Microsoft Excel and Powershell Script.

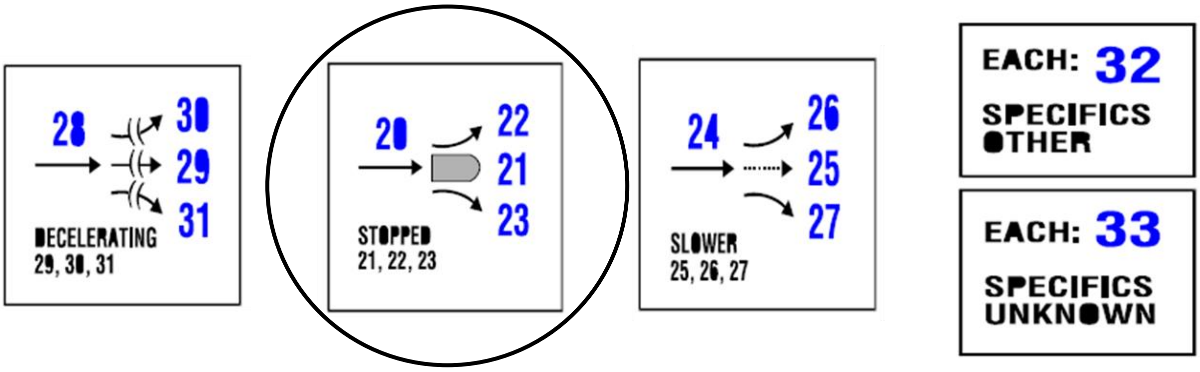

Figure 3.4: Coding number scheme for rear-ends used in the coding manual for the database files

The first problem in a series of problems that was encountered was that all the rear end cases that were obtained by the running the query in SPSS did not have the corresponding EDR reports to go with, i.e. EDR data wasn't available. In depth examination of the available matched rear end EDR reports revealed the second problem that had to be addressed; not all EDR reports contained pre-crash data. Fundamental in the scope of this study, pre-crash information was vital for the what-if simulations. Therefore, matched EDR reports not containing pre-crash information were discarded through manual verification. This drastically reduced the percentage of usable EDR data. The third problem was the identification of the Subject Vehicle (SV) and the Lead Vehicle (LV). None of the EDR files had any information regarding the vehicle in question. (The problem was that if EDR data was recorded for both the vehicles (SV and LV),they weren't necessarily available – some cases had only SV EDR reports, some had only LV EDR reports and a small percentage had both SV’s and LV’s EDR reports). The only way to ascertain which of the vehicles the EDR report belonged to was by entering the details of the case in the NASS CDS case viewer and checking the summary and EDR information of the vehicle in question. Also, some cases had more than two vehicles involved. These cases were also discarded due to complex underlying kinematics and driver behaviour. The final problem was the extraction of data into a usable format (.csv, .xlsx, or .txt). Manual entries from .PDF/.CDR to .xlsx/.csv format had to be carried out due to the grave difficulty in extracting information from .PDF files. After addressing all of the above problems, a total of 23 cases, each containing three pre-crash variables (time series information, speed and brake status) of the SV was obtained.

4 Methodology

This chapter gives a description of the methodology to create and execute 'What-if' or Counterfactual simulations. (From now on these simulations will be called *What-if* simulations). In this study, the analysis was carried out in MATLAB. Figure 4.1 depicts the flow structure of the What-if simulations performed in this study. The flow structure will be described in detail in the subsequent subsections.

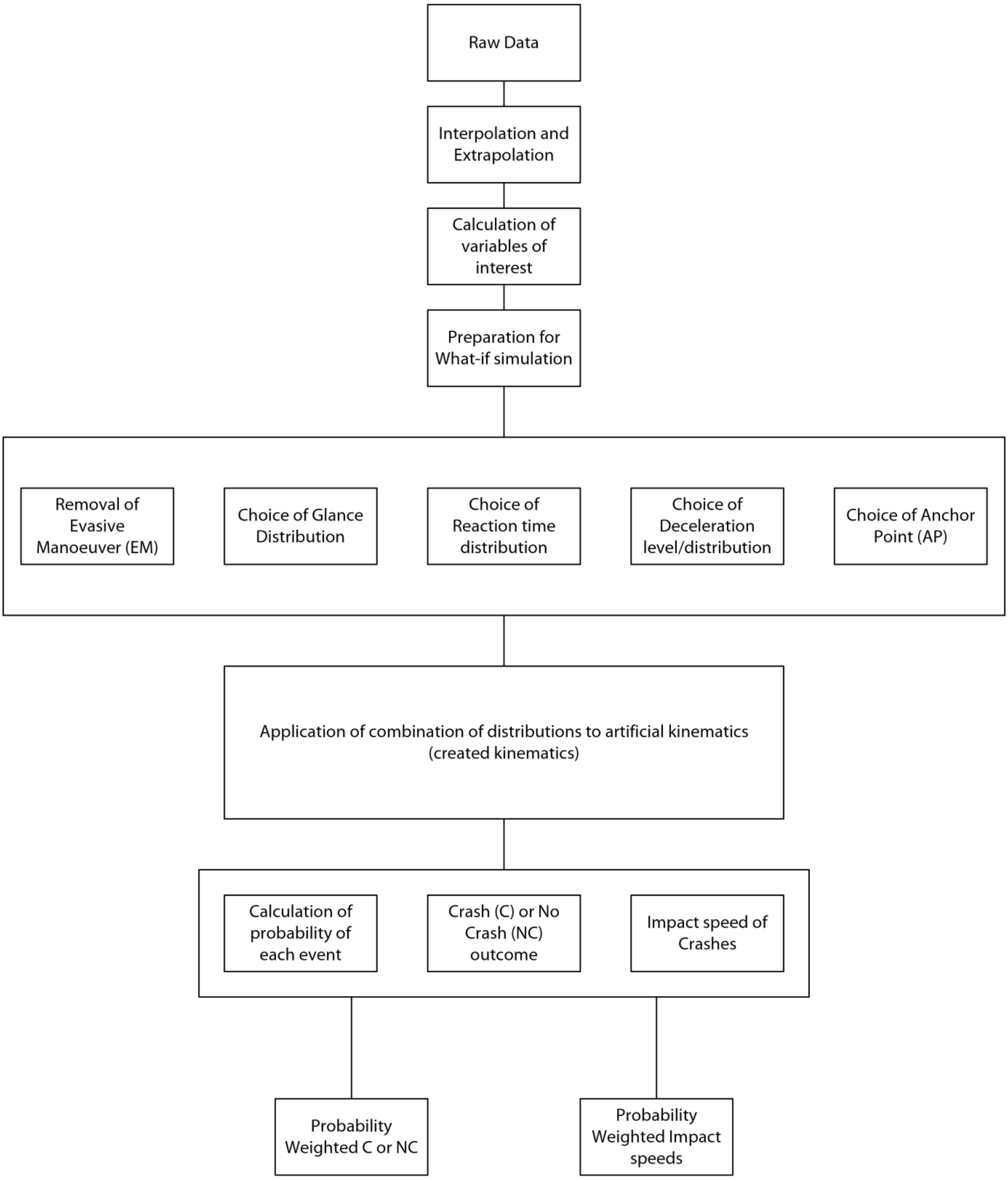

Figure 4.1: Flow Structure of What-if simulation

4.1 Raw data analysis

Once data from the 23 cases was obtained in a usable form (.csv or .xlsx), analysis of the raw data was carried out in MATLAB to ascertain the pre-crash kinematics and driver behaviour. The accelerations and the initial distances were calculated to get an idea of the events that unfolded just before the crash. Figure 4.2 shows the plot of SV speed vs. pre-crash time for the case 2014-76-003-V1 (Here V1 is 'Vehicle 1' as stated in the NASS CDS case viewer, also it represents the 16th case out of the total 23).

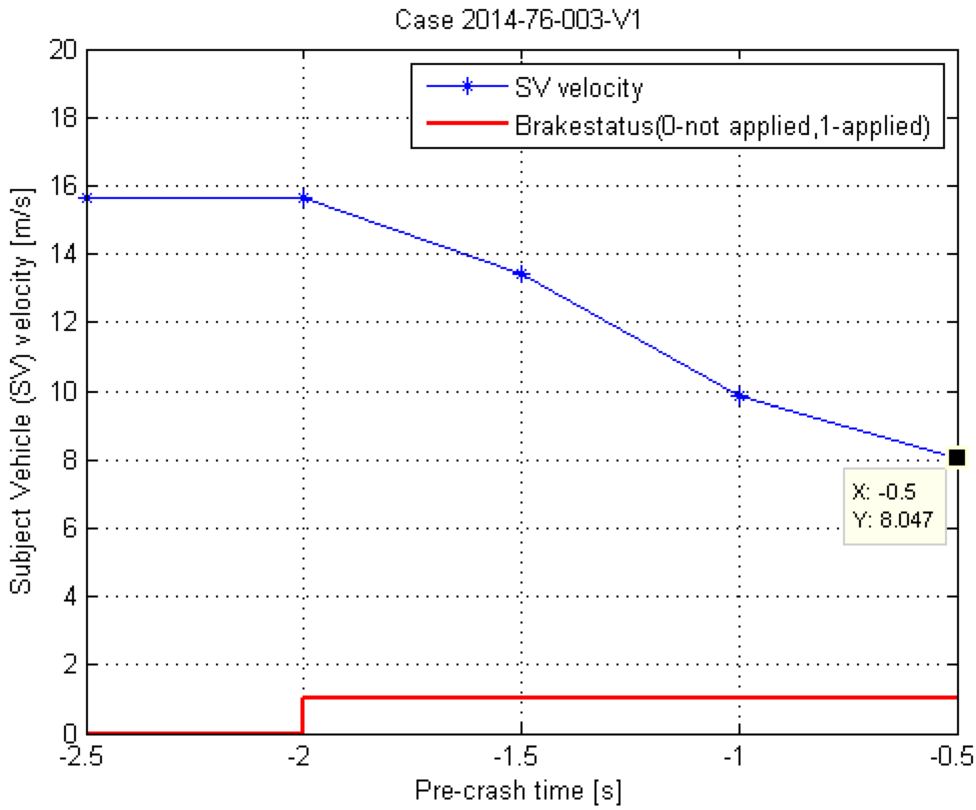

Figure 4.2: Raw data showing SV velocity, pre-crash time-series and brake status

In this case, it can be seen that the raw data contained time-series data only 2.5s before the crash. (The crash point may or may not be at -0.5 s (see Section 6.2.1 and Section 4.2)). The SV applies the brakes at time instant -2 s; the resulting deceleration and brake status can be seen from the blue and red curves respectively. An important assumption to be reiterated is that the LV was assumed to be stationary (0 m/s) for all cases.

4.2 Interpolation, Extrapolation and Variables of interest

Once an impression of the raw data was attained, there was the need to perform interpolation and extrapolation to operate on the data due to the low sampling frequencies and inaccurate crash points associated with EDR data (see Section 6.2.1). Linear interpolation with a time step of 0.01 s was carried out as the What-if simulations required the data to be sampled at a high frequency so that counterfactual outcome information is not lost. Since the crash point was not known due to uncertainty errors, all cases were linearly extrapolated until 0s and its corresponding velocity at t = 0 s was considered to be the original impact speed in each of the 23 cases. Also, the pre-crash time scale was extended in the negative direction (traversing back in time) and the SV velocity at these time instances was set to the value at the start of the original pre-crash time phase so that the position of the chosen anchor point (explained in Section 4.3.3) could be accounted for. This backward extension of time and the setting of the corresponding constant SV velocity had to be done for 7 out of the total 23 cases. Observing Figure 4.3 it can be seen that backward extension of pre-crash time until -4.5 s was carried out as compared to Figure 4.2 which contained SV data starting from -2.5 s. Also, from Figure 4.3, at time instances -0.5 s and 0 s, it can be seen that the impact speed is decreased by 1.8 m/s (6.48 km/h) (see Section 6.2.1).

Once the data was ready to be operated on, the required variables of interest were calculated; relative velocity, relative distance, theta (optical horizontal angle that the lead vehicle has at the eye of the subject vehicle driver; see description below) and thetadot (time derivative of theta) were the primary variables of interest. Relative velocity is the same as the SV velocity as the LV was assumed to be stationary. Relative distance or relative range is the distance of the SV from the LV at each time instant. Calculation of the relative range was assisted by knowing the initial distance of separation between the SV and LV which was obtained by numerically integrating the SV velocity over the pre-crash time frame (see Figure 4.3).

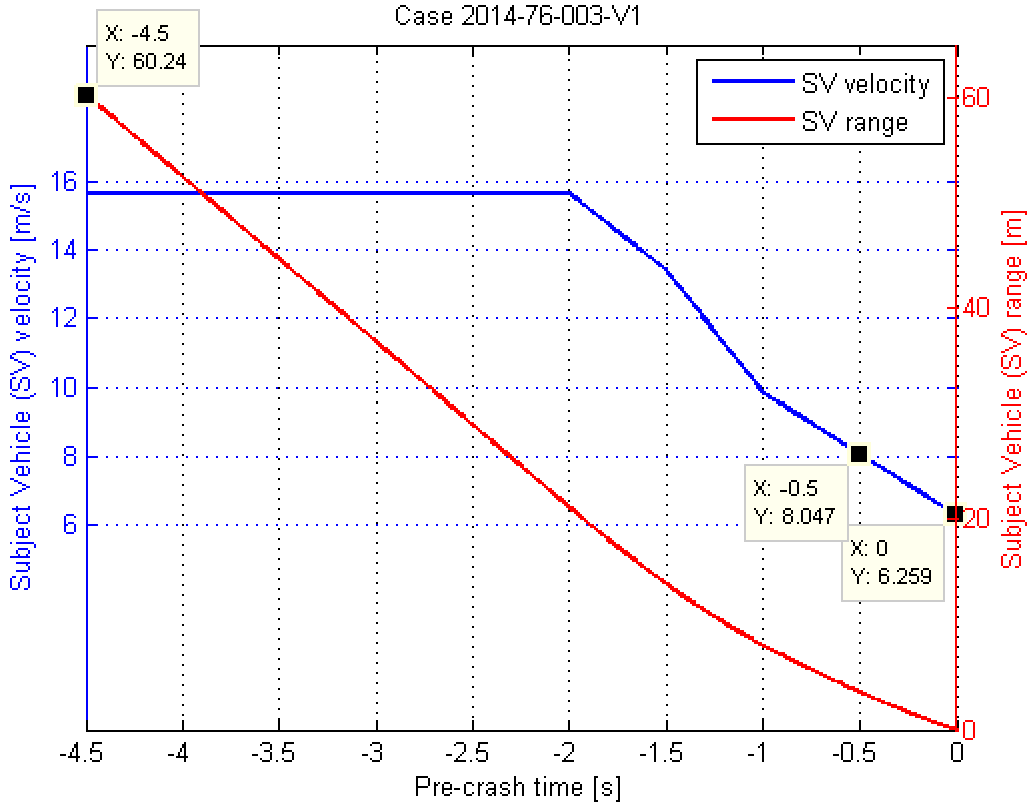

Figure 4.3: Effect of extrapolation on Impact speed (blue) and calculated distance (red).

'Theta (θ)', measured in radians (rad) is known as the visual angle and is defined as the horizontal angle subtended by the driver of the SV onto the LV driver (Lee, 1976). Using the small angle approximation, it is the ratio of the width of the LV (W) to the relative range (r). The width of the LV is assumed to be that of a Sports Utility Vehicle (SUV) equal to 1.8 m (Victor et al., 2015, pp. 28) for all cases in this study. 'Thetadot ($\dot{\theta}$)', measured in radian per second (rad/s) is known as the optical expansion rate or looming and it is the first derivative of the visual angle. This parameter is believed to be the most crucial optical parameter based on which drivers make their decisions (Green, 2016; Markkula et al., 2016). Figure 4.4, shows the visual representation of θ. For the sake of understanding and simplicity, the angle subtended onto the LV is considered from the centre of the SV. In reality, it is the angle subtended by the retina of the driver of the SV who would usually be seated to the left or the right side inside the vehicle depending on the position of the steering wheel.

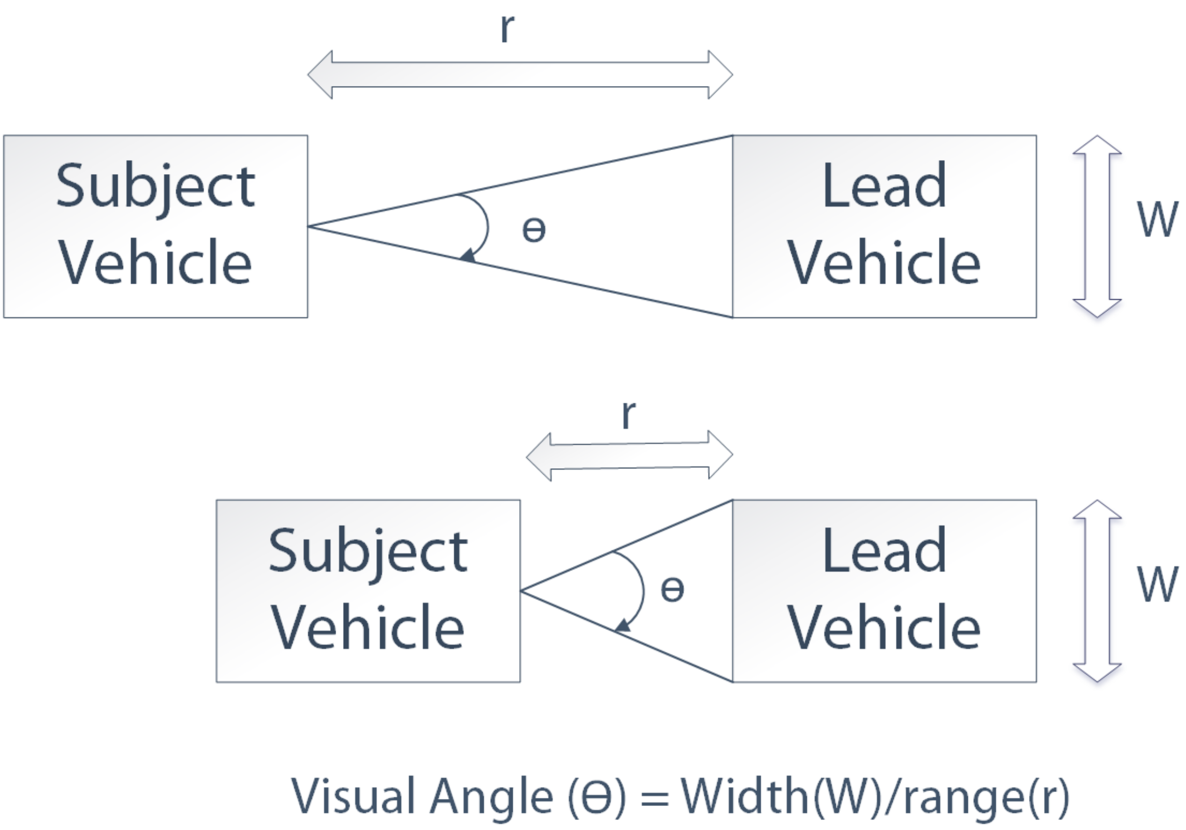

Figure 4.4: Visual representation of theta

4.3 Preparation for What-if simulations

What-if simulations generally require a few decisions to be made based on the kind of outcomes that have to be investigated (see Section 4.4 and Section 4.5). The framework of the simulations in this study is similar to that of Bärgman et al. (2015), Victor et al. (2015) and Bärgman et al. (2016). Outcomes of the choices and combinations of various distributions are explored in this study. Removing the Evasive Manoeuver, selection of distributions for driver-glances, driver-reaction times and deceleration levels are some of the decisions that have to be taken so that the results can be generalized to all drivers and not just a specific driver represented by the original data. Also, the most important decision to be made is the choice of the anchor point (Markkula et al., 2016) because the start of the What-if simulations is exclusively dependent on this metric.

4.3.1 Removal of Evasive Manoeuver (EM) to create artificial kinematics

The first step in progressing to the What-if simulations was to remove the Evasive Manoeuver (EM) that was present in the original crash case. The reason for removing the EM was to maintain generalizability of drivers' braking responses (Bärgman et al., 2016). If the EM had been retained after applying the glances and reaction times, then it would have represented only that particular driver' s braking behaviour and the option to apply a deceleration would have been eliminated.

An EM can be considered as a steering or a braking manoeuver performed by the driver in view of an impending safety critical event. In this this study, an EM will only be considered as a braking manoeuver as modelling a steering evasive manoeuver would require better vehicle models (which include lateral dynamics) to observe it's effect.

Removal of an EM primarily requires the start of the EM to be identified. Bärgman et al. (2016) define the start of an EM to be the first instant before the last steep decrease in acceleration before the occurrence of a crash. However, the EM for all the cases in this study could be recognized solely from the velocity-time plots, i.e. there was no need to observe the acceleration-time plots.

Due to impreciseness in automatic extraction (using algorithms) of EM (Bärgman et al., 2016)[1], the EM start points of all individual cases were extracted through manual annotation. After the EM was identified and removed, the timeseries was extended and the SV velocity was set to the velocity at the instant of EM start (see Figure 4.5). However, some cases did not have an EM associated with it for which the SV velocity was set to the velocity at the crash point. In three extreme cases (Case 20, 21, 22) there were accelerative manoeuvres contrary to the general braking manoeuvres (or no manoeuvres) associated with rear end crash configurations. There were two ways forward with respect to these three cases. One was to extend the SV's velocity after the crash point with the same slope represented in its velocity curve and the other was to set the SV velocity to the velocity at the crash point. The latter was chosen as choosing the former would have resulted in unrealistically high SV speeds.

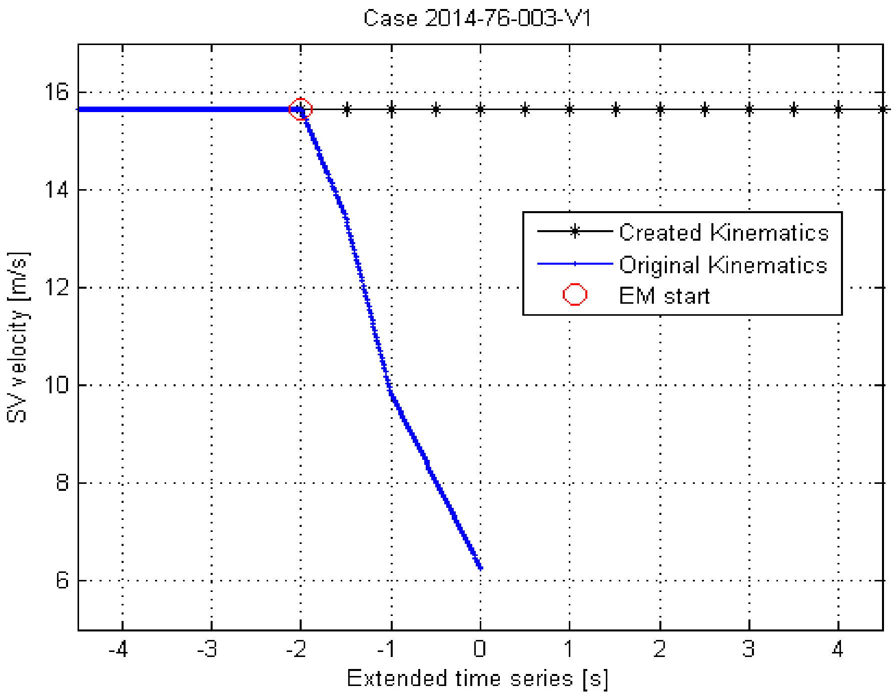

Figure 4.5: Creation of artificial kinematics for What-if simulations

4.3.2 Choosing glance distribution, reaction time distribution and deceleration level

One objective of this study was to observe the effect of different kinds of driver-glance behaviour on the outcomes of crashes and impact speeds. There were two glance distributions that were chosen in this study. One was a Baseline glance distribution (Bärgman et al., 2015) which represented driver glances based on everyday driving. The other was the Rockwell glance distribution which represented the glance behaviour resulting from a documented secondary task of tuning a radio (Rockwell, 1988). Two important terms to be understood are Eyes On Road (EON) and Eyes Off Road (EOFF). The 0 s bin in the distributions is equivalent to EON and the other bins are EOFF (see Appendix A.1). One would argue about the driving

[1] Bärgman et al. (2016) considered automatic extraction initially in their study but reverted back to manual extraction of EM start as they decided that the variability in automatic extraction was too high when compared to manual reviewing by two or more reviewers.

styles of the subjects from whom the data was collected. There are many definitions of driving styles and one of the definitions according to Deery (1999) is the manner in which the people choose to drive with respect to decision making during driving or plainly, the habits of driving gained through experience. A detailed state of the art on the Driving styles addressing the ambiguity in the definitions concerning it is presented by Sagberg, Selpi, Bianchi Piccinini, and Engström (2015). Driving styles and glance behaviours are however assumed to be independent in this study. The distributions of baseline and Rockwell can be found in Appendix A.

Reaction time in this study is considered to be the sum of the perception time and the foot movement time. A reaction time distribution with bins of 0.4 s, 0.5 s and 0.6 s was created. These values were chosen mainly based on the findings of Markkula et al. (2016) as the most of the data in their study was centred on a value of 0.5 s (see Appendix A.2 for explanation). Values based on Green's (2000) findings (see Section 2.4) were not considered in this study. As the research community was divided on the use of pre-defined reaction time, a decision was taken to go with the findings of Markkula et al. (2016).

There was a vast amount of literature available to choose a deceleration level. Bärgman et al. (2015) use -8 m/s^2 representative of hard decelerations. Kusano and Gabler (2011) found out the average deceleration of driver's braking in rear end scenarios to be around -5 m/s^2. Wege, Thomson, & Piccinini (2016) used deceleration of -6 m/s^2 to replicate non-ideal vehicle braking performance. Kiefer et al. (2005) found the average deceleration of drivers' braking with different configurations to be -5 m/s^2 for speeds lower than 64 km/h. A decision was taken to proceed forward with a value of -6 m/s^2 based on the report of summaries of technical documents made by Wege et al. (2016) as the concept of non-ideal braking performance was pragmatic enough to be applied in the what-if simulations.

The reason for choosing a single value of deceleration level rather than a distribution of deceleration levels was mainly to get a clear picture of how the glance and reaction time distributions affected the outcomes. The reaction time distribution was created to maintain generalizability. Brake actuator delay is not considered in this study and tire-road friction coefficient is assumed to be 1 for braking manoeuvres.

4.3.3 Choice of anchor point (AP)

The choice of anchor point (AP) is the most important aspect of the What-if simulation. This point determines how the distributions affect the outcomes. From the findings and assumptions made in Bärgman et al. (2015), Markkula et al. (2016) and Victor et al. (2015), an AP can be described as the last instant of time before which a driver's off-road glance would not affect the outcome of the situation. In this study, thetadot = 0.01 rad/s was chosen as the anchor point. This choice of an optical parameter based AP was motivated by the results obtained by Markkula et al. (2016) where they conclude that drivers don't usually brake until the thetadot value reaches 0.01 rad/s and brake responses are potentially based on the urgency of the situation processed optically by the drivers rather than purely context independent kinematic dependencies (e.g. Lead Vehicle Brake Light Onset) (Green, 2000).

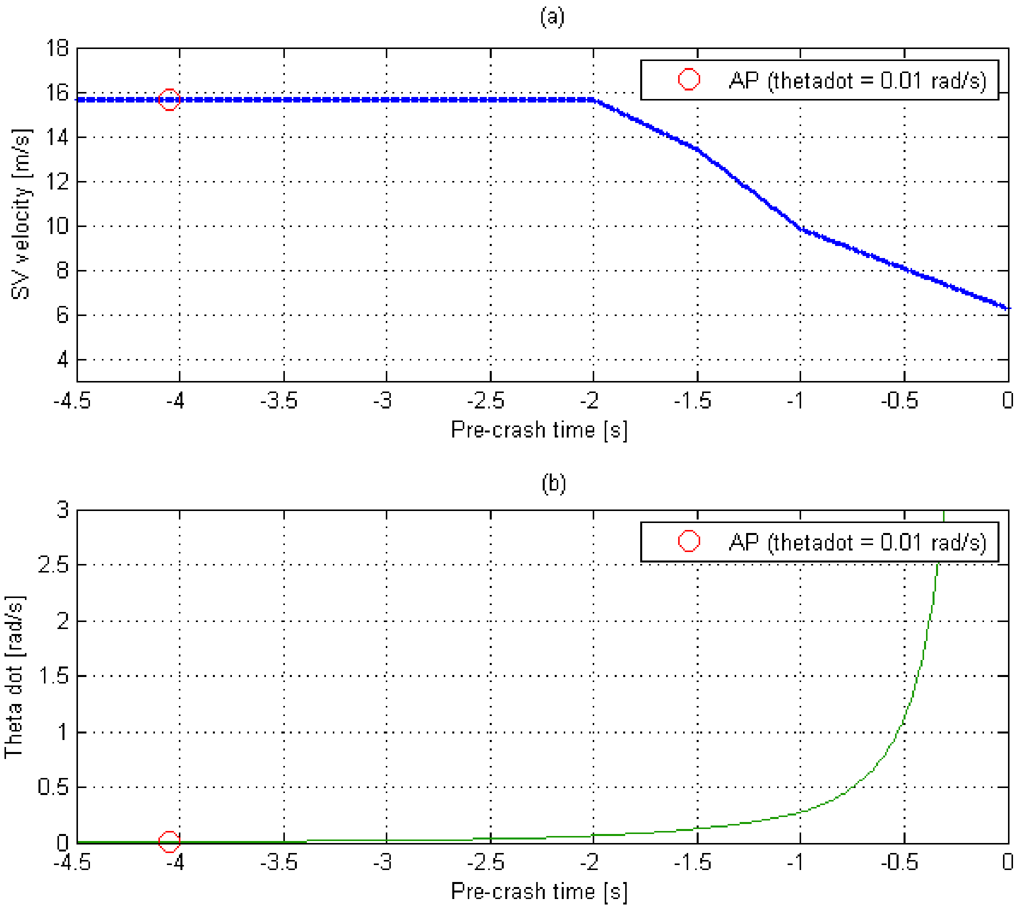

Figure 4.6: (a) Anchor point as seen from SV's perspective, (b) Variation of thetadot w.r.t SV kinematics

Figure 4.6 (a): Position of the AP represented by a red circle in the SV's kinematic profile in Case 2014-76-003. Figure 4.6 (b): Variation of optical expansion rate (thetadot) just before the crash; an exponential rise tending towards infinity is seen as the crash point approaches.

4.4 Performing the What-if simulations: application of the combination of distributions to the artificial kinematics

The What-if simulations were ready to be performed after the glance distribution, reaction time distribution and deceleration level was decided. Since the objective of the study was to primarily monitor the effect of glance behaviours on the outcomes, two batches of simulations were performed for each case. One batch of simulations was run with a combination of Baseline glance distribution and the aforementioned reaction-time distribution and deceleration level and the other batch was run replacing the Baseline glance distribution with the Rockwell glance distribution. The number of counterfactual events depended on the size of the distributions and would be equal to the product of the no. of bins in each distribution. For example, consider that there are 62 values of glance duration (baseline) and 3 values of reaction time. The resulting number of counterfactual events is 186 (62 *3). Each simulation event would begin at the AP resulting in an outcome indicating a Crash (C) or No-Crash (NC). Impact speeds were then calculated for every event that resulted in a crash.

The order of application of the distributions to the framework was as follows: value of glance duration (s), value of reaction time duration (s) and value of deceleration (m/s^2). The chosen order is pragmatic in nature which mimics drivers' behaviour in real life (Note: In the simulation, the order does not really matter as all combinations of values of the distributions are simulated). This was ensured by implementing algorithms in a MATLAB script.

4.4.1 Calculation of Crash/No-Crash metric and Impact speeds

The calculation of whether an event resulted in a Crash or No crash involved simple logic. If the relative distance between the SV and the LV was 0 m after the application of the deceleration, then that particular event resulted in a crash. On the other hand, a relative velocity of 0 m/s would infer that there was no crash in the corresponding event. As a result, crash events had corresponding impact speeds associated with them. A non-pragmatic assumption that was made here was any impact speed greater than 0 was considered as a crash; no matter how the low the value was (up to the third decimal point greater than 0). This was done for theoretical consistency. Also, the mean of the impact speeds of all the events were calculated and a single averaged impact speed was calculated for each case.

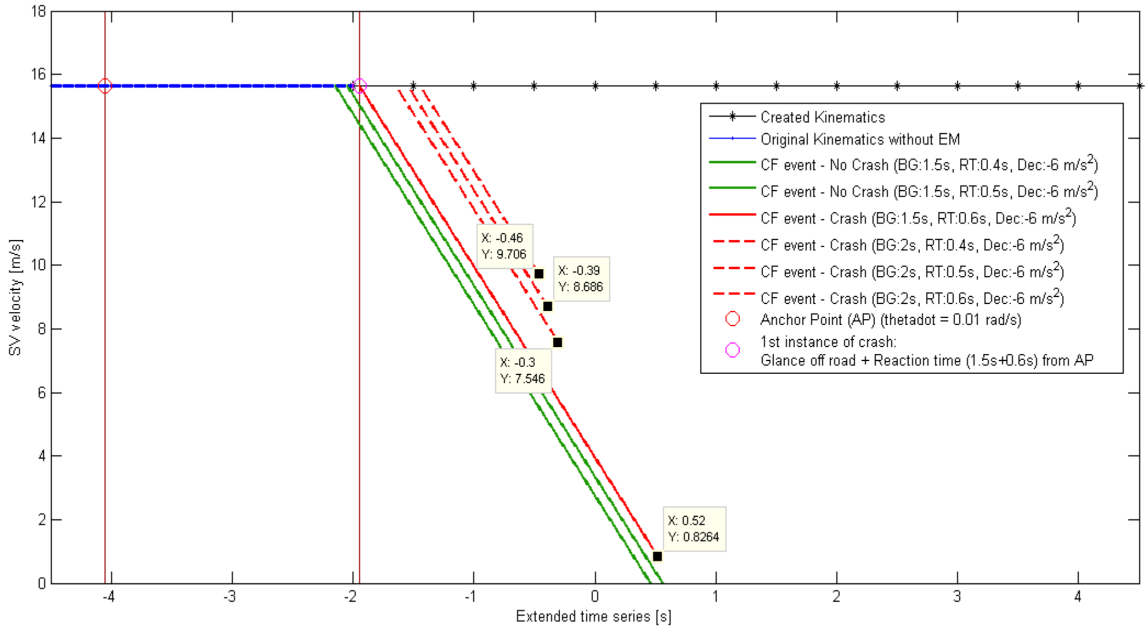

Figure 4.7: What-if simulation showing six Counter-Factual events resulting in Crash and No Crash

A small part of the What-if simulation incorporating six Counterfactual events can be comprehended visually from Figure 4.7. This configuration is extracted from Case 2014-76-003 for which the Baseline Glance distribution (denoted by 'BG'), Reaction time distribution (denoted by 'RT') and Deceleration level (denoted by 'Dec') was applied. In this particular set of events, the glance off road duration of 1.5 s and 2 s with all the values of reaction time (0.4 s, 0.5 s and 0.6 s; short reaction times based on findings of Markkula et al. (2016)) along with a constant deceleration value of -6 m/s^2 is shown. In this particular crash case (Case 2014-76-003-V1), the first instance of a crash occurs when the glance off-road duration is 1.5 s with a reaction time of 0.6s (represented by the magenta circle). Two vertical lines on the markers (circles) were placed for visual convenience.

Varying time durations (BG + RT) give rise to outcomes represented by the red (Crash) and green (No Crash) curves. Since the red curves represent crashes, they have impact speeds associated with them which can be seen from the Y-coordinates where the curves terminate. The green curves representing Non crash events, end up on the X-axis signifying zero impact speeds which suggests that the deceleration level was enough to bring the SV to a halt before a collision.

4.4.2 Calculation of the probability of each event (based on distribution)

The probability of the occurrence of an event depended on the probabilities of values in the distributions used. The total number of counterfactual events depended on the size of the distributions as stated earlier in Section 4.4. Each distribution had a set of probabilities associated with them. Each bin's corresponding measure had a probability associated with it. For example, consider the Baseline Glance distribution; 145 subjects glanced off the road for 0.6 s. The total number of subjects in the Baseline Glance distribution was 5992. The probability of having a glance off road for 0.6 s was therefore 145/5992 which equalled 0.0242. Similarly the bins of the reaction time distribution had its respective probabilities associated with it.

Once the probabilities for each distribution were found, the joint probabilities of the combinations of bin values were calculated. The product of the singular probabilities gave rise to the joint probability of that combination. As an example, the details of the combination which resulted in a crash stated in Figure 4.7 are as follows: Baseline glance off road of 1.5s corresponded to a probability of 0.0045 and reaction time of 0.6s corresponded to a probability of 0.1521. The product of the two terms points to a joint probability of 0.0006 (0.0045 * 0.1521). Similarly all other possible combinational joint probabilities were calculated so that Crashes could be weighted accordingly (see Section 4.5).

4.5 Calculation of probability weighted Crash or No crash metric and Impact speeds

Weighting the crashes and non-crashes based on their corresponding probabilities was the final part of the What-if simulations. It was imperative that the counterfactual events were weighted otherwise there would be no significance of the contribution of the distributions which again places emphasis on the choice of distributions in general. In this study a crash was represented by '1' and a non-crash by '0'. For each case, each crash or no crash event was multiplied by its corresponding joint probability and summed up together. This resulted in each case having value greater than or equal to 0 and less than or equal 1. For example, considering the case stated in Section 4.4.2 (BG = 1.5s, RT = 0.6s) the joint probability of 0.0006 was multiplied by 1. A combination of BG = 2s, RT = 0.6 s having a joint probability of 0.0010 (calculated as mentioned earlier in Section 4.4.2) was also multiplied by 1. Similarly the joint probability of the other crashes were also found and then summed together. (Note: the joint probabilities of the non-crashes were found out too, but on multiplication with 0, their value was 0 and hence did not have an effect). A value closer to 1 suggested that there were more number of crashes resulting from the counterfactual outcomes. Values close to 0 implied a greater percentage of outcomes not resulting in a crash.

The impact speeds of the events leading to a crash were also weighted by multiplying the joint probability. The individual weighted impact speed of each event was then summed up and a single weighted impact speed for each case was calculated. For example, in the configuration shown above (BG = 2s, RT = 0.6s), the impact speed of 9.7064 m/s (see Figure 4.7) was multiplied by 0.0002 giving a value of 0.0022. Similarly, the configuration of BG = 1.5s, RT = 0.6 s producing an impact speed of 0.8264 m/s was multiplied by its corresponding joint probability of 0.0006 producing a value of 0.0005. Also, the impact speed of the non-crashes (0 m/s) was also multiplied by their corresponding joint probabilities. Refer to Appendix B for an account of the counter-factual events for Case 16 (Baseline Glance distribution). Similarly, another batch of simulations incorporating the same methodology was performed replacing the Baseline glance distribution by the Rockwell glance distribution.

5 Results

5.1 Crash or No Crash outcome

5.1.1 Effect of glance distributions on outcomes

Figure 5.1 shows how the glance behaviours affect the Crash or No Crash metric of the outcomes. As stated in Section 4.5, the data points lie between 0 and 1. All 23 cases were considered to observe the spread of crash or no crash metric with respect to the two distributions (Baseline and Rockwell). The Rockwell glances produced greater number of events resulting in crashes in most of the cases as opposed to the Baseline glances.

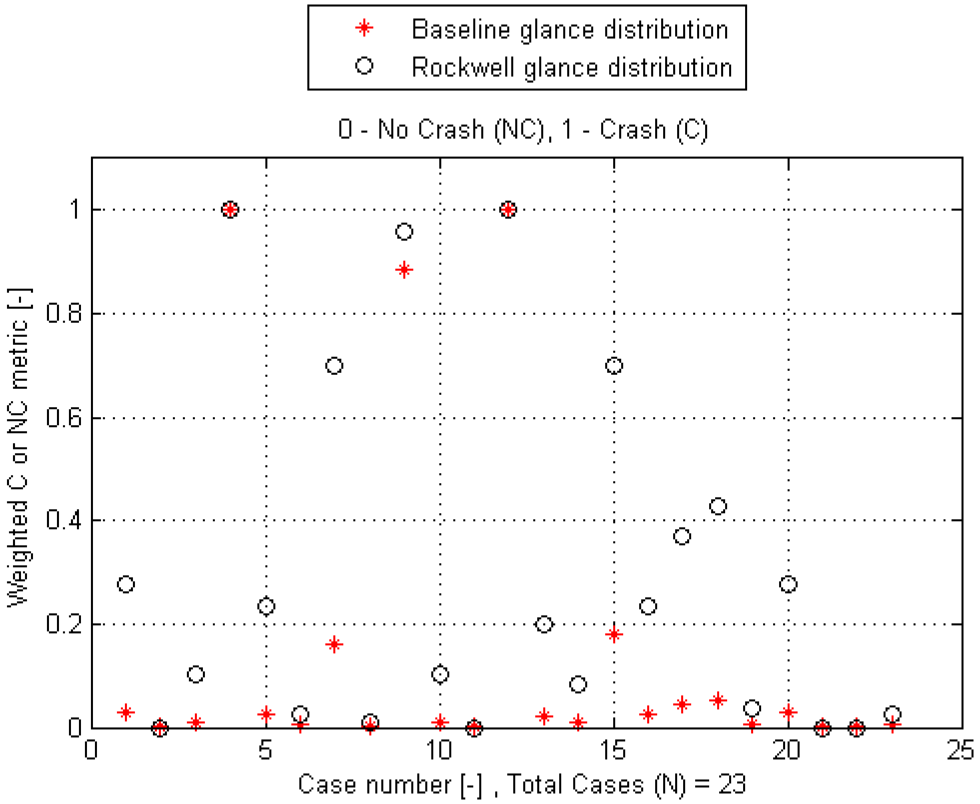

Figure 5.1: Effect of glance distributions on Crash or No Crash metric

From Figure 5.1, it can be seen that cases 2, 11, 21 and 22 produced no crashes in any of their respective counterfactual events when the Rockwell distribution was applied. Although these points seem to overlap with the points of the baseline glance distribution, it wasn't the case. Minimal impact speeds were associated with the baseline glance distribution for these cases (of the order of 0.001 m/s) (see Section 5.2.1) due to a small proportion of the baseline glance distribution which contained very long glances (of the order of 6s). Case 4 and 12 on the other hand produced crashes for all counterfactual events for both distributions which suggested a high crash severity (high initial speed/low relative distance).

From Figure 5.1 it can be noticed that Case 4 and 12 produce crashes in all the counterfactual simulations irrespective of the glance distribution applied. This indicates that the SV was travelling at a really high velocity and a deceleration of -6 m/s^2 would not have prevented the collision. However, the impact speed would have been mitigated.

Case 2 did not have an EM present. The SV travelled at a speed of 6.66 m/s (23.97 km/h) (extrapolated value) and collided with the LV. From the simulations it is clear that if the driver of the SV had elicited any kind of braking response, he/she would have prevented the collision which leads to the inference that the driver of the SV might have been severely distracted or sleeping.

Case 11 on the other hand had an EM present. Since the EMs were removed for all cases, there was no exception here. But since none of the counterfactual outcomes produced a crash, the case had to be investigated further. A closer look at the kinematics revealed a startling detail: there might have been a brake malfunction or a discretization error or a possible Anti-Lock Braking System (ABS) intervention. Figure 5.2 shows the kinematic signature (no extrapolation i.e. raw data) of the case. The distance of separation between the SV and LV was around 40 m. It is believed to be discretization error as the slopes at which the speed reduces is the same during the application of the brakes and when brakes are not applied (Speed reduction due to lift off from accelerator pedal). It could also signal ABS intervention as highlighted in yellow. The braking starts at -2 s before the crash. The staircase form is synonymous with the activation of ABS cycles which was verified by a method proposed by Kiencke and Nielsen (2005). Since the periods of constant speed (as opposed to decreasing) in the ABS cycle were relatively long, it could mean that the ABS controlled the brake pressure of the wheels really cautiously so that the wheels would not lock up. This behaviour could translate to icy or slippery roads (i.e. friction coefficient less than 1). Although, there was a collision, it should be noted that probably the ABS mitigated the collision by reducing the impact speed. Had there not been ABS present, the impact speeds could have been higher. From the driver's perspective, this seemed to be an unlucky situation: a moment of distraction/inattention at a crucial time coupled with a slippery road surface. It is important to keep in mind that these are possible hypothetical inferences of what might have happened based on the evidence present since the context of the situation preceding the crash is not known.

Case 21 and 22 were similar to Case 2, the only difference was that there was an accelerative manoeuver present prior to the collision which could suggest that the driver engaged the throttle instead of the brake or it could also signify that the driver fell asleep with his/her leg on the throttle. None of the counterfactual outcomes resulted in crashes as the SV speed setting after the EM of 6.70 m/s (24.12 km/h) with a distance of separation of 33.75 m were ideal conditions for a braking manoeuver to prevent a collision. It can be said that the original crash was solely due to the accelerative evasive manoeuver. No conclusions on original crash causation can be made by looking at the counterfactual events of the cases not resulting in crashes because the initial distance between the SV and the LV would also influence the counterfactual outcomes in addition to low SV speed setting after the EM.

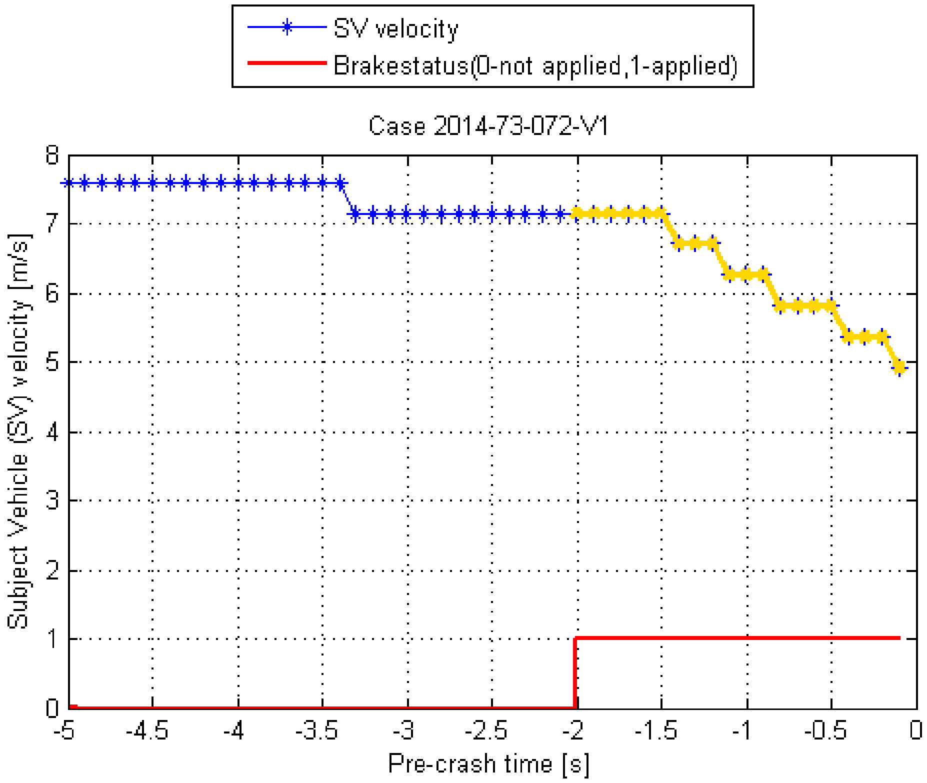

Figure 5.2: ABS intervention (yellow) in Case 11 (raw data)

When impact speeds were plotted, Cases 9, 14 and 17 were removed due to unreasonable levels of deceleration after extrapolation which resulted in speeds less than 0 m/s. This will be talked about in Section 6.2.1.

5.1.2 Effect of weighting on Crash or No Crash metric

Figure 5.3 shows the difference between weighted and unweighted crashes. The weighting will not affect the non-crashes of the counterfactual events as they have a value of 0 associated with them (Multiplying with the joint probability would not matter). A striking disparity can be observed with the crashes resulting from the baseline glance distribution with 50% reduction of crashes after the probability weights were applied. Also, a 10% rise in the no. of crashes can be noticed arising from the Rockwell distribution. Weighting is an integral procedure which has to be done to enable any form of generalization and if it is not, each individual What-if simulation is considered a crash in its own right – which is unrealistic (Bärgman et al., 2016). That is, if weighting is not performed, the simulations would just represent a set of combinations of parameters applied and therefore the what-if simulations would completely lose representativity.

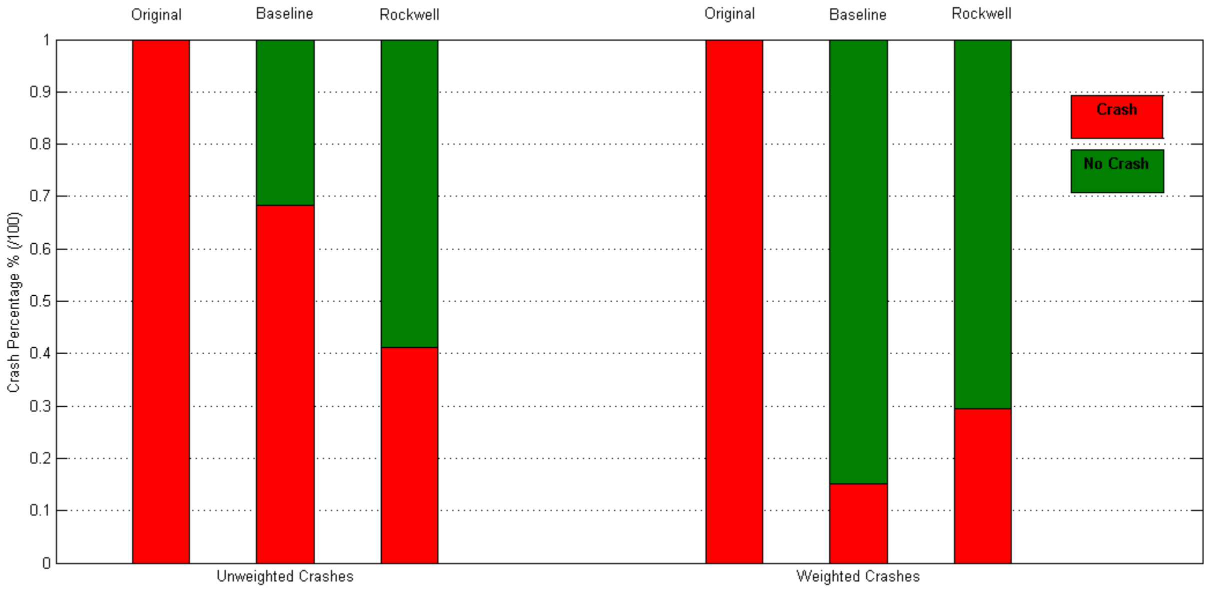

Figure 5.3: Comparison of Weighting (Probability) and No Weighting on crashes

5.2 Impact speeds of Crashes

5.2.1 Effect of glance distributions on Impact speeds

A Cumulative Distribution Function of impact speeds was constructed for the Original crash data, Baseline crash data and the Rockwell crash data as seen in Figure 5.4. The cumulative distribution shown illustrates the percentage probability (*100) of finding an impact speed less than or equal to a chosen impact speed. Note that the number of cases considered here was 16. Since four cases (2, 11, 21 and 22) had no crashes arising from the counterfactual events (Rockwell distribution) as mentioned in Section 5.1.1, they did not have impact speeds linked with them and as a result, they were theoretically irrelevant to be considered for the analysis of impact speeds. Three other cases (Cases 9, 14 and 17) contained unreasonable levels of deceleration observed from the original data. When data processing was performed on these cases (see Section 4.2), negative impact speeds were brought about by extrapolation. Since original impact speeds were plotted for reference, these cases were disregarded entirely for this plot. However, they were considered for other analyses (crash or no crash metric) because the removal of the EM (see Section 4.3.1) essentially eliminated the erroneous part of the data.

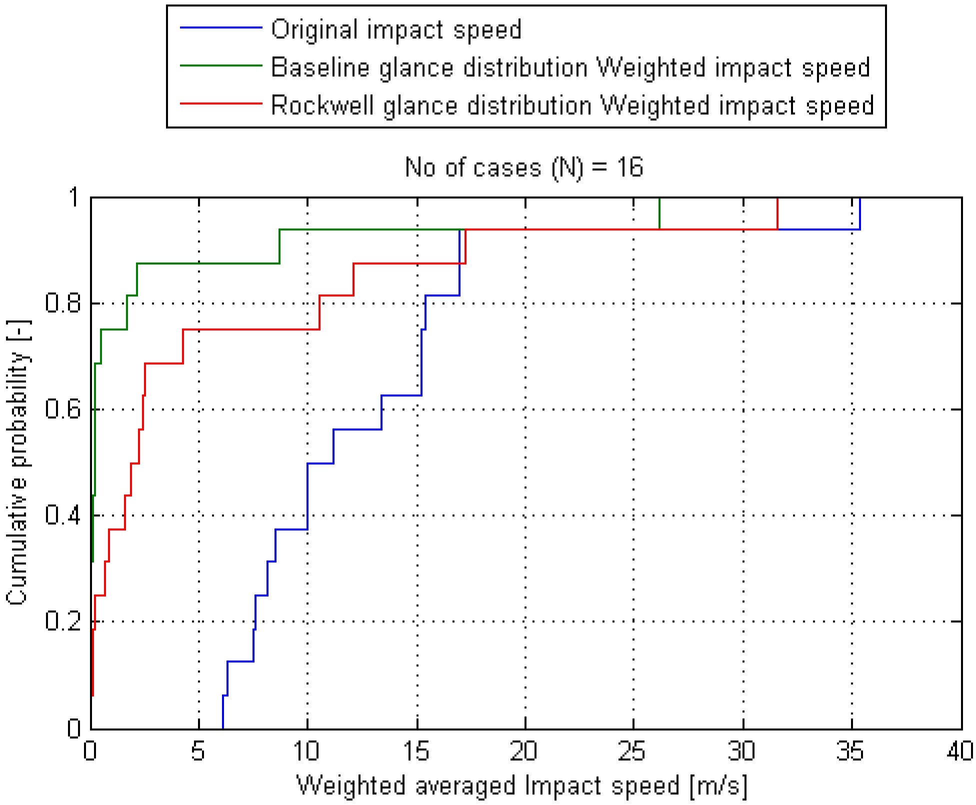

Figure 5.4: Cumulative Distribution Function of Weighted impact speeds

A large gap can be seen between the original impact speed and the impact speeds resulting from the modified events which imply that there is a large difference in impact speeds when compared to the original cases (which gives an idea of how severe the original crashes were). It can be perceived that 70% of the crashes from the baseline glance distribution and Rockwell glance distribution have an impact speed less than or equal to 2 m/s (7.2 km/h) and 4 m/s (14.4 km/h) respectively whereas 70% of the original crash profiles had an impact speed less than or equal to 16 m/s (57.1 km/h).

To visualize the differences between central values of impact speeds of the two distributions and the original impact speeds, box plots were put together to observe the spread of the impact speed data. Figure 5.5 shows box plots for original, baseline and Rockwell impact speeds (weighted).

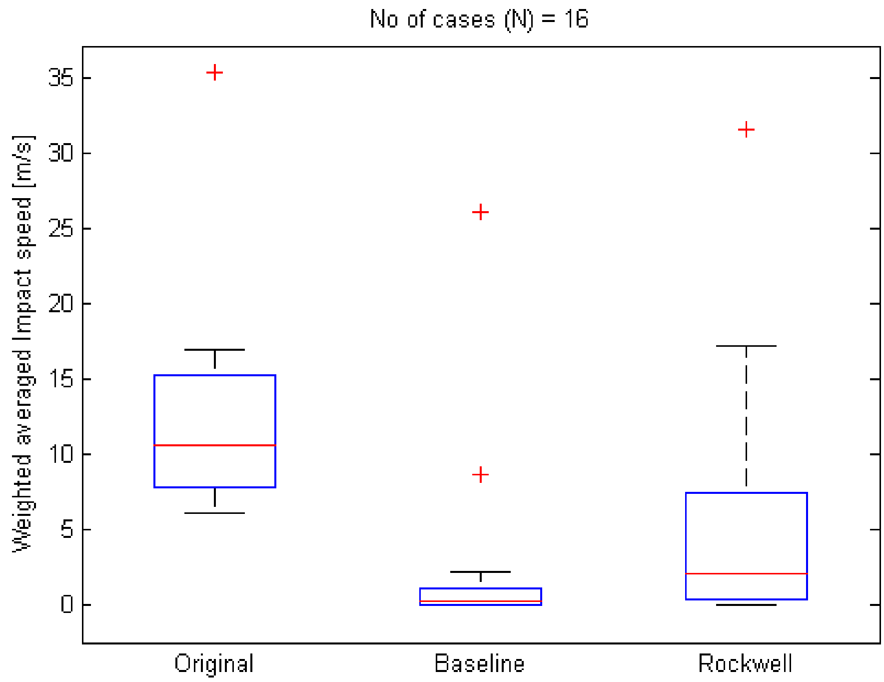

Figure 5.5: Box plots of weighted impact speeds of Original, Baseline and Rockwell crashes

The interquartile ranges of original, baseline and Rockwell crashes were 7.43 m/s (26.74 km/h), 1.03 m/s (3.70 km/h) and 6.98 m/s (25.12 km/h) respectively. The whisker length was set to a default value of 1.5 times the interquartile range. The impact speed data of original, baseline and Rockwell crashes appear to be highly skewed as the red median lines are not at the centres of the boxes. The Rockwell crash data seemed to have the highest spread of data in contrast to the baseline crashes with the exceptions of outliers. Closer inspection of the baseline box plot (see Figure 5.6) showed that the 25th percentile was almost 0.06 m/s (0.21 km/h) and the 50th percentile (median) was 0.21 m/s (0.75 km/h).

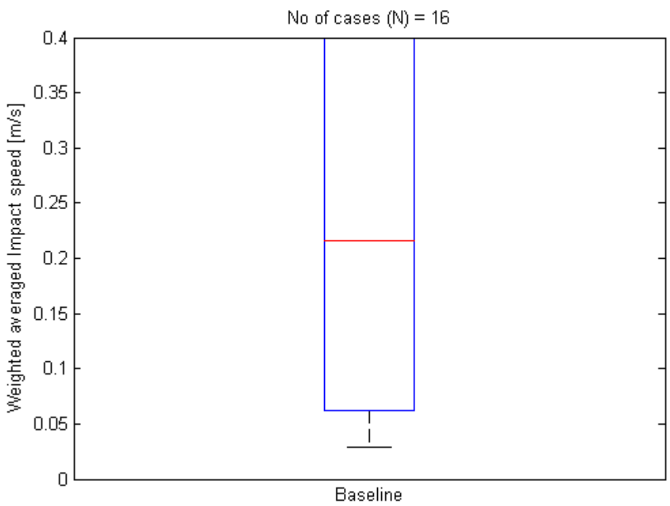

Figure 5.6: Close-up of Baseline box plot showing 25th and 50th percentile

5.2.2 Effect of weighting on Impact speeds

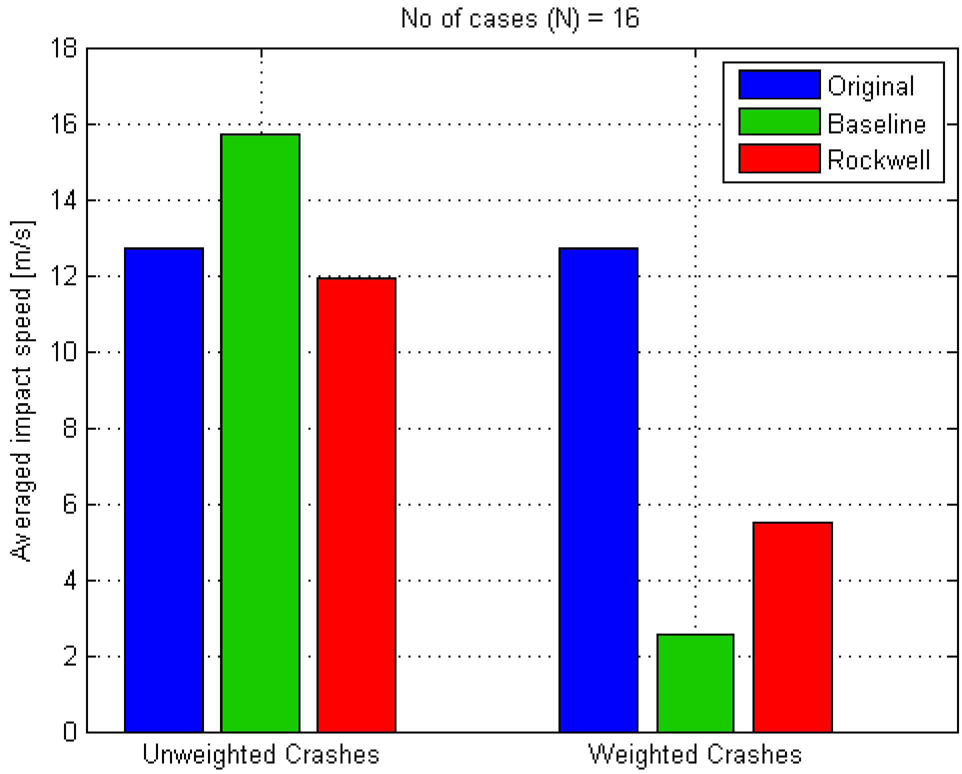

Figure 5.7: Comparison of weighting (probability) and no weighting on Impact speeds

Figure 5.7 shows the comparison of unweighted averaged impact speed versus weighted averaged impact speed of 16 cases. Conflicting results can be seen with the unweighted impact speeds as opposed to weighted impact speeds of both distributions. The average unweighted impact speeds of baseline and Rockwell were 15.72 m/s (56.59 km/h) and 11.92 m/s (42.91 km/h) as compared to weighted impact speeds of 2.54 m/s (9.14 km/h) and 5.52 m/s (19.87 km/h) respectively. The average impact speed of the 16 original cases was also plotted as a reference. This observation clearly shows the significance of applying weights when performing What-if simulations and is synonymous with the findings stated in Section 5.1.2.

6 Discussions

6.1 Effect of glance distributions and weighting on outcomes and impact speeds

The reason for the lower crash metric for the Baseline glance distribution in Figure 5.1 is due to the nature of the Baseline glance distribution itself. The Baseline glance distribution is equivalent to normal everyday driving where drivers keep their eyes on the road (EON) almost all the time. In the Baseline distribution (see Appendix A.1.1), 80% of the subjects kept their eyes on the road (i.e. a glance duration equal to 0s) compared to 30% of the subjects with EON from the Rockwell distribution.

As far as weighting the cases is concerned, it was imperative that the counterfactual events were weighted based on the probability of the individual combinations of parameter distributions. Without weighting the counterfactual events would just be a combination of a set of configurations without any representation of the significance of the glance behaviours and other distributions which is evident from Figure 5.3 and Figure 5.7. Therefore the choice of the distributions is really important. The more representative the distribution, the more meaningful the simulation.

6.2 Limitations of study

6.2.1 EDR data

As representative as it may be, EDR data is plagued by a variety of shortcomings. Firstly, the way EDR data is coded in the database can sometimes be misleading. For example, when the search query for stationary (or ‘stopped’) rear end crashes was run, EDR reports from the ‘decelerating’ and ‘slow’ rear end cases were also included (see Figure 3.3 for categorization). This was discerned by reviewing the data of the LV (as mentioned in Section 3.3, availability of EDR data of both vehicles (SV and LV) involved in the crash was rare). These cases were discarded and in view of this point, it should be noted that when data of the LV was not available, it was assumed to be stationary (which is mostly true because the case in question was available in the LVS rear end category in the first place). Also, when data of just one vehicle was available, the case viewer had to be checked to confirm whether the vehicle in question was the SV or LV. The information regarding Vehicle 1 (V1) and Vehicle 2 (V2) being the SV or LV was misrepresented in the case viewer summary itself.

Secondly, since pre-crash velocity is obtained from wheel speed sensors of the vehicle, EDR data can be deceiving due to underestimation and/or overestimation during hard braking (>1g) and rapid acceleration. Only hard braking was relevant for this study as the focal point was rear end crashes. Hard braking often results in wheel lockup when the tyre-road friction coefficient is less than 1 (slippery roads) which leads to underestimation of speeds due to slip which subsequently leads to overestimation of deceleration values (Bare, Everest, Floyd, & Nunan, 2011; Scanlon et al., 2015).

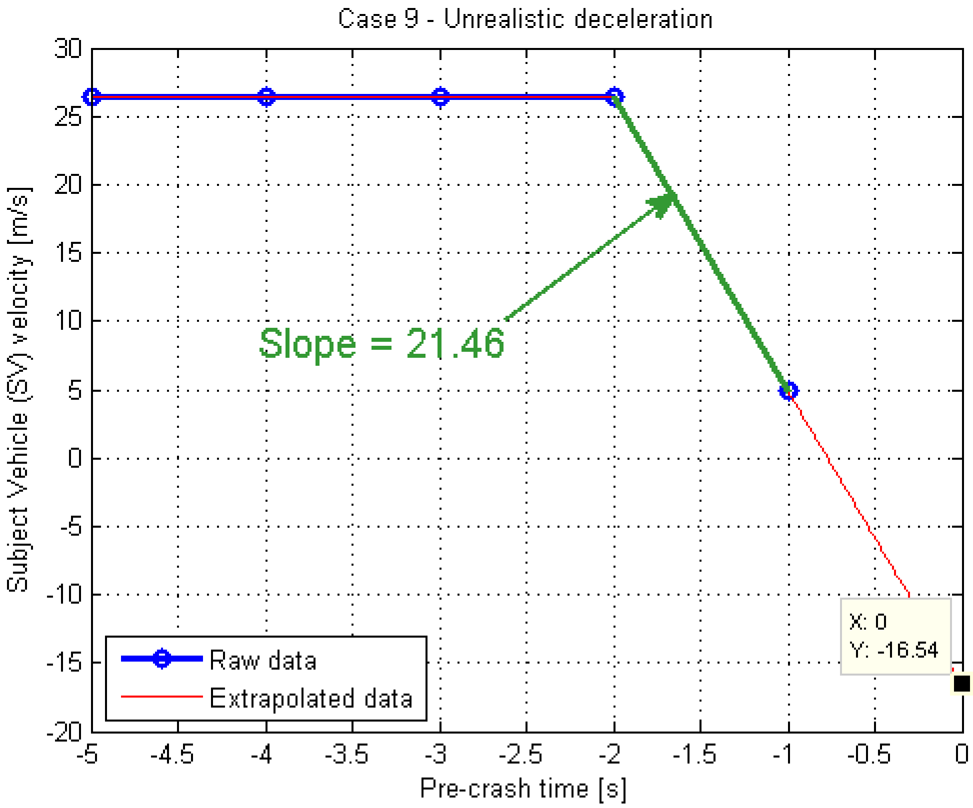

Figure 6.1: Velocity-time curve showing overestimated deceleration of Case 9

This phenomenon was exhibited by case 9 as seen in Figure 6.1 and was the reason for which it was discarded from the What-if simulations. Calculating the slope of start and end points of the EM in the velocity-time curve of case 9 resulted in an unrealistic deceleration value of 21.46 m/s^2 (shown in green).

Lastly, the most concerning source of uncertainty in the EDR pre-crash record is the error due to asynchronicities in recording of time series information prior to a crash. Pre-crash data will be collected continuously by an EDR and when there is an airbag deployment event, the last 5 seconds of data gets written to memory. It should however be noted that in the event of a crash, the EDR time scale is unfortunately not synchronized with the actual time scale of the crash (Wilkinson, Lawrence, Heinrichs, & King, 2006). What this means is that when there is a collision, the algorithm governing airbag deployment is enabled to signal the restraint system to deploy the airbags. This is the actual point of impact of the crash which is not the same as the last recorded point of the pre-crash time scale. This uncertainty coupled with low sampling frequencies makes the impact point nearly impossible to determine. Based on the work of Wilkinson et al. (2006), Kusano and Gabler (2011) account for this uncertainty by time shifting the pre-crash EDR data by one half the sampling rate. In another study, Scanlon et al. (2016), attempt to reduce this uncertainty further by performing the time shift and then extrapolating to determine impact speed. They also state that there is no way of actually determining the exact crash point irrespective of the operations performed. Therefore, in this study an approximated impact speed of the original cases was determined by only extrapolating the last recorded data point of the pre-crash speed.

6.2.2 Glance distribution, reaction time distribution, deceleration level and Anchor Point (AP)

As mentioned earlier in Section 4.3.2, the glance distribution, reaction time distribution and deceleration level was chosen and created based on literature; the point to be noted here is that these distributions were primarily influenced by car following scenarios. Also, the definition of an AP by Bärgman et al. (2015)

was in the context of car following scenarios. However, based on the findings of Markkula et al. (2016), the AP was defined on the basis of visual looming cues which implies the validity of the choice of AP for any rear end configuration (car following or LVS).

With the exception of a few studies on decelerations with respect LVS scenarios (test track experiments from Kiefer et al. (2005) and EDR lead vehicle stopped scenarios from Kusano and Gabler (2011)), there is a shortage of literature concerning LVS rear end crashes. NHTSA (2007) also report similar stats under the 100 car NDS, and out of 7024 observed rear end events, only 27 resulted in crashes, 450 resulted in near crashes and 6547 were just incidents. Even though this seems to be an alarmingly low number of crashes, a notable statistic was that 22 out of the 27 crashes (81 %) were Lead Vehicle Stopped rear end crashes. This indicates that the driver could have most probably been distracted severely as looming cues increase really fast for a stationary vehicle; it subsequently implies that the choice of AP needs to be explored further for Lead Vehicle Stopped scenarios.

A reaction time distribution was created on the basis of urgency metrics (optical cues) (Markkula et al., 2016) and not on Lead Vehicle Brake Onset (Green, 2000; Kiefer, Leblanc, et al., 2005). The findings of Markkula et al. (2016) do not completely justify the chosen values of 0.4 s, 0.5 s and 0.6 s as these times are synonymous with an expected hazard rather than an unexpected one. Since the decision to apply the distribution at the start of the AP was followed, it is most likely the driver would have been reacting to an unexpected hazard. In theory, these values might hold true for the baseline glance distribution but in the case of the Rockwell glance distribution where drivers have eyes off road longer compared to baseline, the reaction times would be on a higher side (>1s) due to the onset of an unexpected hazard (Green, 2000) which Markkula et al. (2016) claim otherwise through their findings. Also, if the driver perceives the hazard sufficiently early, he/she might be gradual on the deceleration level (i.e. lower deceleration level).

To conclude, due to lack of knowledge of the relationship between the glance, reaction time and deceleration distributions, it was assumed that the distributions are independent from each other. This assumption does not hold good in real life situations and it precludes the validity of the results of the simulation to an extent, but the integrity of the methodology framework remains intact, in line with what Bärgman et al. (2016) describe. Judgement on the results of the simulations should therefore be reserved until further studies are undertaken to determine how these distributions are correlated. Also, a very low number of events were used in this study which is again, another factor to reserve judgement.

6.3 Sensitivity analyses

6.3.1 Choosing a different Anchor Point

A Sensitivity analysis choosing thetadot = 0.02 rad/s as the AP was performed to observe changes in crash percentage and impact speeds as compared to thetadot = 0.01 rad/s. The analysis was carried out to account for worst case driver behaviour where the driver looks away from the road during a critical time where it is still ‘just’ possible to prevent a crash. A wide variety of glance configurations could have been applied. An alternative approach would have been to apply glance behaviour much earlier than the AP so that the off road glances overlap with the chosen value of AP which would have provided a different set of results which might have been less severe in nature.

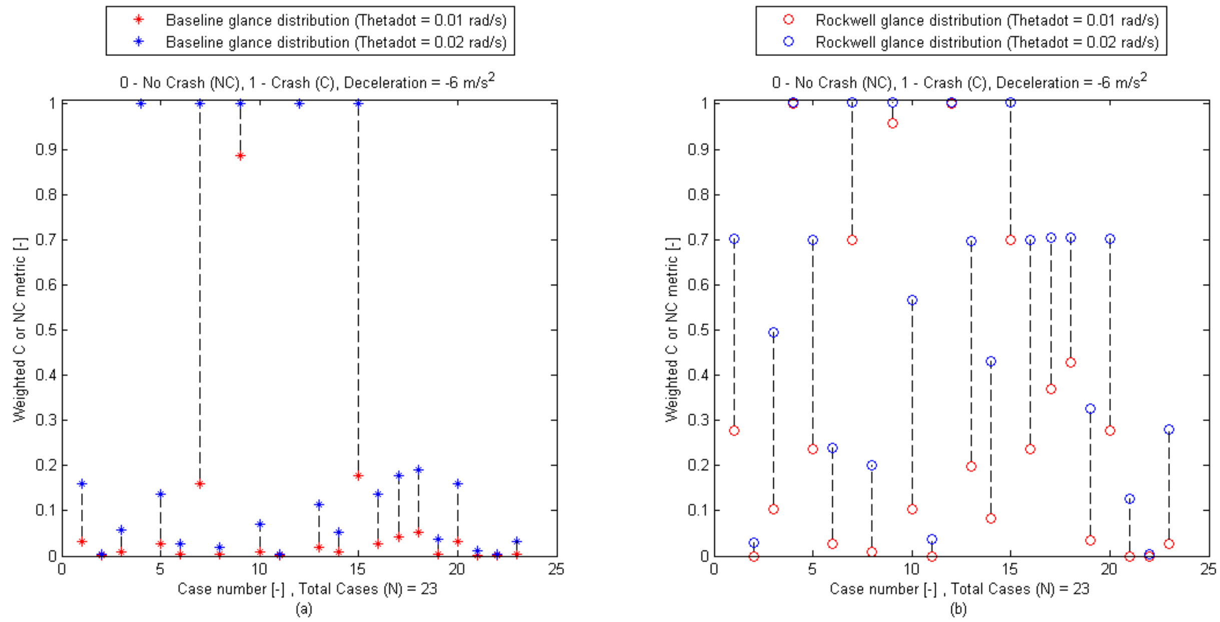

Figure 6.2: Crash metric for different Anchor points (a) Variation of crash metric: Baseline Glance distribution (b) Variation of crash metric: Rockwell Glance distribution

However, since the chosen dataset of EDR data mostly contained severe crashes, worst case configuration of glance behaviour was applied (i.e. the driver initiates the off road glance at the AP). With the AP chosen as 0.01 rad/s for the entire study, it can be noticed from Figure 5.4 that there is a large difference in impact speeds of the original crashes and the crashes due to the glance distribution inspired counterfactual events. There was no question that increasing the value of thetadot to 0.02 rad/s would produce greater percentage of counterfactual crashes (see Figure 6.2 (a) & (b)) and higher impact speeds. On an average, the overall percentage increase of crashes due to the AP of 0.02 rad/s in the Rockwell glance distribution was 30% (see Figure 6.2 (b)). The percentage increase of crashes in the Baseline Glance distribution was around 15% but if case 7 and case 15 were excluded (both of which had an increase of around 80%), the percentage increase in crashes drops to a value less than 10% (see Figure 6.2 (a)). But the point of interest lay in observing how close the impact speeds would be with respect to the original impact speeds.

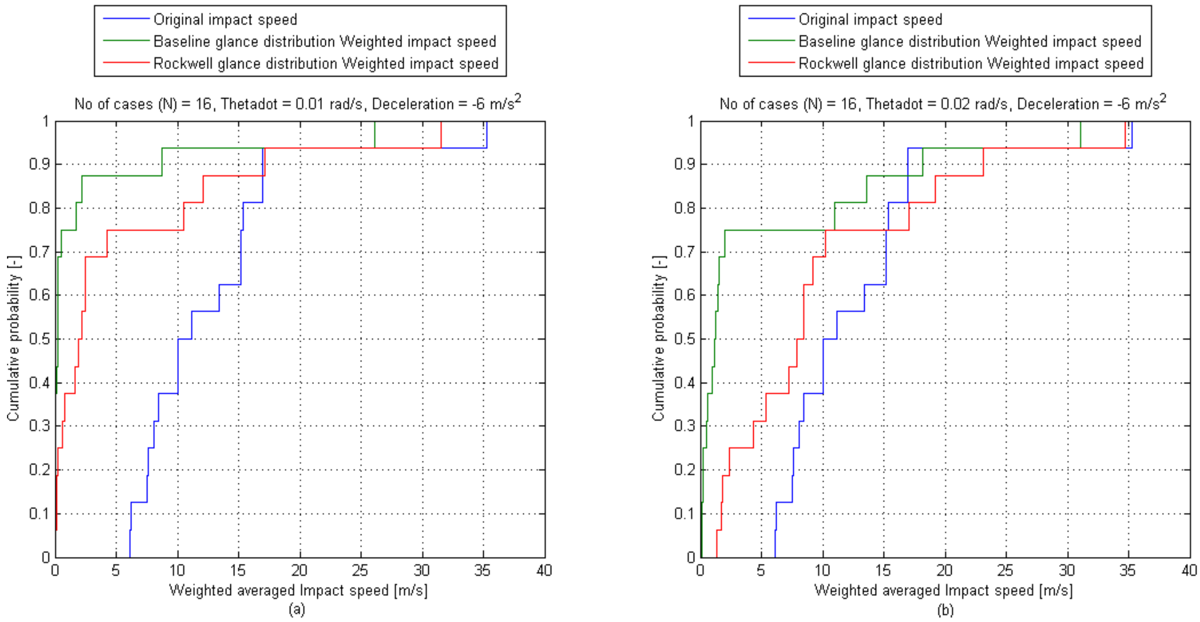

Figure 6.3: Comparison of Cumulative probability of impact speeds with AP = 0.01 rad/s and 0.02 rad/s (a) Weighted averaged impact speeds for thetadot = 0.01 rad/s (b) Shift in impact speeds for thetadot = 0.02 rad/s

Figure 6.3 (a) and (b) show the shift in impact speeds associated with the Baseline and Rockwell distribution for 0.01 rad/s and 0.02 rad/s respectively. Note that the number of cases considered here is 16. Figure 6.3 (a) (the same as Figure 5.4) is placed alongside Figure 6.3 (b) for the sake of comparison to observe the shift of impact speeds toward higher values. Comparing the two Figure 6.3 (a) and (b), it can be seen that 70% of the crashes in Figure 6.3 (b) have impact speeds less than 3 m/s (10.8 km/h) and 11 m/s (39.6 km/h) for Baseline and Rockwell distribution respectively as compared to crashes having speeds less than 2 m/s (7.2 km/h) and 4 m/s (14.4 km/h) for Baseline and Rockwell glance distributions for thetadot = 0.01 rad/s (see Figure 6.3 (a)). It is clear that the Rockwell distribution was affected more than the Baseline and it could be agreed that it is likely a more representative glance distribution to be associated with EDR data as the impact speeds of the Rockwell distributions are closer to the original impact speeds.

Note however, that in all of these simulations it is assumed that the only crash causation mechanism is the driver looking away from the forward roadway. Aspects such as drowsiness (e.g., sleeping drivers), or scenarios where the SV driver expectancy of the LV moving out of the way may have played a major role (Engström et al., 2017) is not considered. Further work should consider these aspects and also extend the application to car-following situations rather than LV stopped scenarios.

6.3.2 Choosing a different deceleration level

Another sensitivity analysis choosing a harder deceleration level of -8 m/s^2 was performed to observe changes in crash percentage and impact speeds as compared to a deceleration level of -6 m/s^2. The AP was set to thetadot = 0.01 rad/s for this analysis. The rationale behind performing this analysis was that drivers' usually braked hard (usually up to the vehicle's limit) prior to an imminent collision and this value was chosen to be -8 m/s^2 according to the choices made by Bärgman et al. (2015) where they assumed that the vehicle's braking performance was ideal (braking at limits, dry surface).

As it can be seen from Figure 6.4 (a) and (b), running the simulations with a deceleration of -8 m/s^2 instead of -6 m/s^2 reduces the crash percentages notably in the case of Rockwell distribution when compared to Baseline, the reason being that the drivers kept eyes on road most of the time in case of Baseline distribution as they might have recognized the threat fairly early and braked accordingly based on the situation. Only cases 4 and 9 have drastic reductions in crash percentages as they had extremely high speeds (around 100 km/h) in the pre-crash phase. The distance of separation in both cases was around 100 m. Therefore, a high deceleration level would have naturally mitigated/prevented the crash.

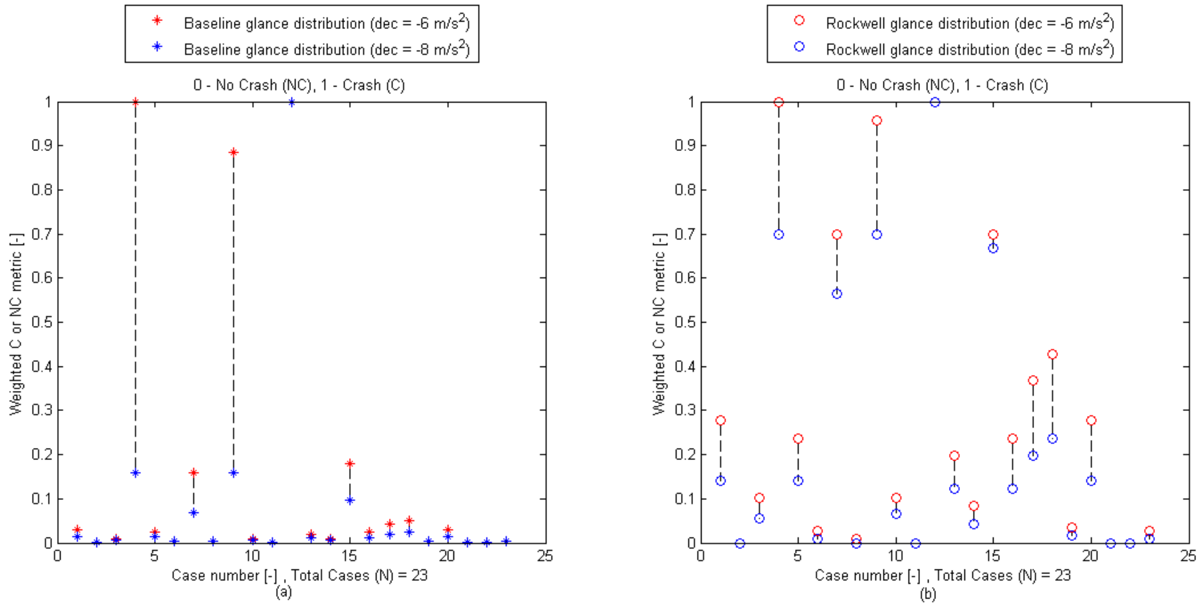

Figure 6.4: Crash metric for different deceleration levels (a) Variation of crash metric: Baseline Glance distribution (b) Variation of crash metric: Rockwell Glance distribution

Figure 6.5 (a) and (b) show the shift in impact speeds associated with the Baseline and Rockwell distribution for -6 m/s^2 and -8 m/s^2 respectively. Note that the number of cases considered here is 15; in addition to the already excluded cases (9, 14, 17 and 2, 11, 21, 22), case 8 also had to be excluded from the impact speed analysis as a deceleration of -8 m/s2 did not produce a single crash for any of its counter-factual events. Again, Figure 6.5 (a) (the same as Figure 5.4 excluding case 8) is shown for the sake of comparison.

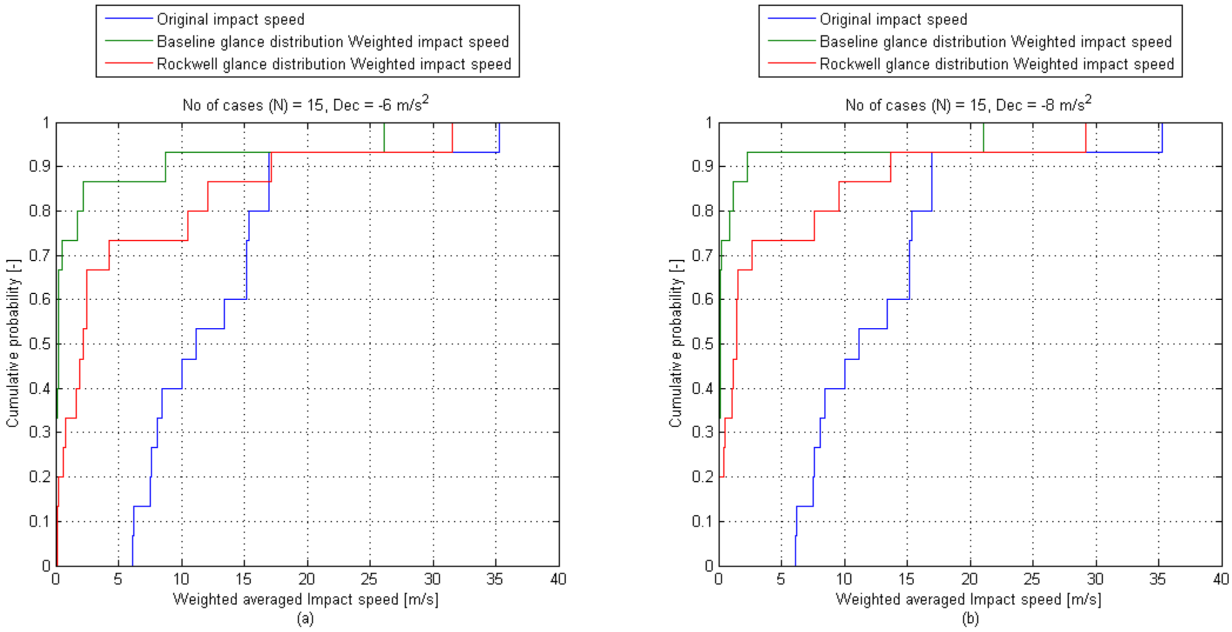

Figure 6.5: Comparison of Cumulative probability of impact speeds (thetadot = 0.01 rad/s) with deceleration = -6 m/s² and -8 m/s² (a) Weighted averaged impact speeds with deceleration = -6 m/s² (b) Shift in impact speeds for deceleration = -8 m/s²

From Figure 6.5 (b), it can be seen that 70% of crashes have an impact speed less than 1 m/s and 3 m/s for Baseline and Rockwell glance distribution respectively as compared to 2 m/s and 4 m/s (Figure 6.5 (a)).

In conclusion, various analyses could have been performed in addition to these with one of them being a combination of a high thetadot value (0.02 rad/s) coupled with a hard deceleration (-8 m/s²), but the essence of this study was to showcase the versatility of the current simulation framework revolving around a central aspect: to observe the effect of glance distributions on crash outcomes. That is, the choice of deceleration, or maybe a distribution of decelerations, is important for counterfactual analysis, but so is the choice of anchor points and a variety of other parameters – the counterfactual simulation method needs more validation to be truly useful in estimation of risks or benefit estimation of safety systems.

7 Conclusions and Future work

Counterfactual or What-if simulations using real world crash data from EDRs and glance behaviours from NDS were performed. The chosen crash configuration was LVS rear end scenarios and its corresponding data was extracted from the NASS CDS crash database for use in the simulations. The glance distributions were obtained from previous studies inspired by NDD whereas the reaction time distribution and deceleration level was created and chosen respectively based on previous studies. The anchor point was also chosen based on findings from a recent study. The distributions were applied to the simulations with a single deceleration and their outcomes (crash and no crash) were observed. The outcomes were weighted based on the calculated joint probabilities. The effect of the glance behaviours was observed from the results when compared with the original crash data. A framework for the evaluation of safety benefit of ADAS was showcased: If a safety system is to be applied, its safety benefit could be observed by comparing the percentage of crashes avoided with respect to the original data.

This study addressed the need to merge data sources by providing a methodology framework using EDR data of LVS rear end scenarios and driver glance behaviours obtained from NDS to assess the effect of different glance behaviours (Baseline glance distribution and Rockwell glance distribution) on crash outcomes and impact speeds through use of What-if simulations. This framework could be considered as a promising way forward for active safety ADAS evaluation as it retains crash representativity and incorporates driver behaviour which is vital to design use cases. Also, care should be taken to know exactly what is required out of the What-if simulations. A powerful tool in every right, What-if simulations can tend to be misleading if the target goals are not properly defined and care is not taken to address the details of parameterization and generalization.

The reason for combining data sources was that EDR data provided detailed pre-crash information but provided little context information. There was a need to incorporate context information and assess the impact on counterfactual outcomes with reference to the original crashes. Hence, glance behaviours from NDS were included to simulate driver glance behaviour prior to crashes. A hypothetical reaction time distribution and deceleration level were created and chosen based on literature as mentioned previously. The results would be more valid if realistic reaction time and deceleration distributions based on stationary vehicles were available and possibly, if car-following scenarios would have been used rather than lead vehicle stopped (LVS) scenarios. Actually, the need to consider different anchor points should be considered in LVS rear ends as the visual looming cues would be stronger due to the fast closing rate of the SV with respect to the LV. It may be that the driver model used as a basis in these simulations are considerably more realistic for car-following than for LVS scenarios, and that a good driver model for LVS is still missing.

The findings show that the Rockwell distribution is a much more indicative glance distribution of what might have happened in the original crash as it contains a larger percentage of crashes and also because it is closer to the cumulative distribution curve of original impact speeds – if all crashes are assumed to be due to SV driver off-road glances. This was due to longer glances away from the road compared to baseline glance distribution which is due to the nature of the distribution itself, but possibly even more so, the much lower percentage of on-road glances in the Rockwell than in Baseline. Also, the point of showing the effect of baseline distribution was to give the readers an idea about a possibility of what the drivers of the original crash did not do. Had the drivers of the original crashes followed an everyday driving inspired glance profile (like the baseline distribution), he/she probably would have not crashed – given that the driver model used in the counterfactual simulation is reasonably correct. But again this inference was deduced based on the results obtained.

This study also highlights the limitations of EDR data in addition to showcasing its potential in representing real crash information. The biggest problem regarding EDR data is the asynchronous nature of the recorded pre-crash data. If the pre-crash time scale and the actual crash time scale were aligned (i.e. synchronized), EDR data would have been a greater data asset for researchers trying to ascertain precise timing of braking manoeuvres of drivers before crashes.

As far as safety benefit is concerned, the evaluation of safety systems was performed by testing it in simulator experiments by defining target cases (Ljung Aust, Engström, & Viström, 2013). Wege et al. (2016) present an extensive report on safety benefit of an emergency braking system making use of What-if simulations by defining use cases and target scenarios. Inspired by this aforementioned report, a sound framework for predictive evaluation for estimating the benefit of active safety ADAS using EDR data, glance behaviours and counterfactual simulations is established. Systems like FCW and AEB can be applied and its benefit estimated. The usage of EDR data represents pre-crash kinematics of actual crashes in contrast to NDD which represents a great percentage of near-crashes than crashes. This study complements the work of Bärgman et al. (2016) who use NDD to evaluate the safety benefit of Forward Collision Warning (FCW), Autonomous Emergency Brake (AEB) and FCW+AEB together.

Based on the findings, limitations and the foundations laid in this study, proposals for future work are stated:

1. Models of active safety systems like FCW and AEB should be applied to estimate their safety benefit. Implementation of a basic system would still reveal the percentage of crashes prevented and/or mitigated impact speeds.
2. Different categories of rear end crash configurations (Lead Vehicle Slowing, Lead Vehicle Decelerating) should be included in further analyses and calls for studies on driver behaviour (and development of driver models) in stationary LV (LVS) scenarios should be made in parallel.
3. Modifications of glance behaviour like removing longer glances could be incorporated based on prevailing kinematics. (For example, if the SV speed/distance is above a certain threshold, glances greater than certain duration should be removed to account for self-regulation of drivers). This should be done when more context data is available from NDS.
4. Rear end scenarios are relatively easy to model; the simulations could be extended to much complex crash categories like Run off road, Turn across path and Straight crossing path scenarios.
5. As larger datasets with respect to EDR data and NDD become available, the identification and extraction of the EM should become automatic. One possible way forward here would be to explore artificial neural networks and machine learning algorithms.
6. Inclusion of vehicle and environment models (road, terrain) in the what-if simulations should be done in the future.
7. Finally, a final recommendation vital to the validity of the simulations is the exploration of the relationships between glance distributions, reaction time distributions and deceleration distributions. It is crucial to conduct studies to understand how these distributions are correlated with one another.

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Appendix A Applied Distributions

Two types of distributions were applied to the What-if simulations which consisted of Glance distributions and reaction time distributions.

A.1 Glance Distributions

The glance distributions represent the glance behaviours of drivers in real life inspired from NDS. Two glance distributions were considered separately and applied along with a created reaction time distribution based on literature.

A.1.1 Baseline Glance Distributions

The baseline glance distribution is shown in Figure A.1. The baseline glance distribution is synonymous with everyday driving where drivers have their eyes on road (EON) most of the time. This data is from trips of drivers' daily commute to work, highway drives and miscellaneous drives. The data collected reported users having off-road glances of upto 6 seconds. This distribution was taken from Bärgman et al., (2015).

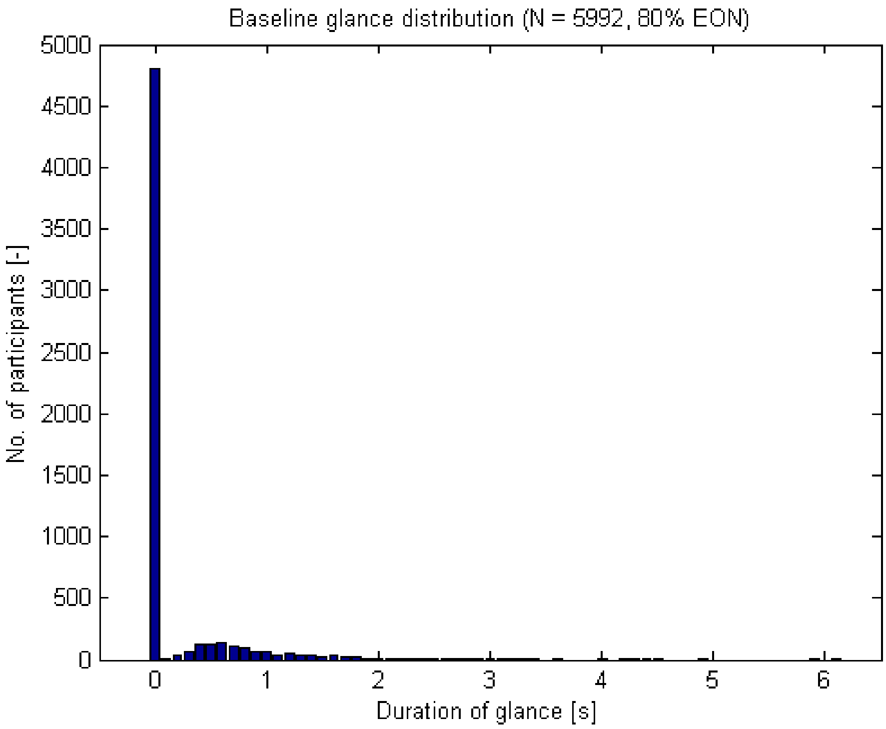

Figure A.1: Baseline glance distribution

The total number of subjects (Sample size 'N') that were considered was 5992. The 0s bin in Figure A.1 represents that the subjects had eyes on the road. As expected, this is considered to be normal behaviour of everyday driving. 20% of the subjects had eyes off the road (EOFF). A better representation of the 20% can be seen in Figure A.2.

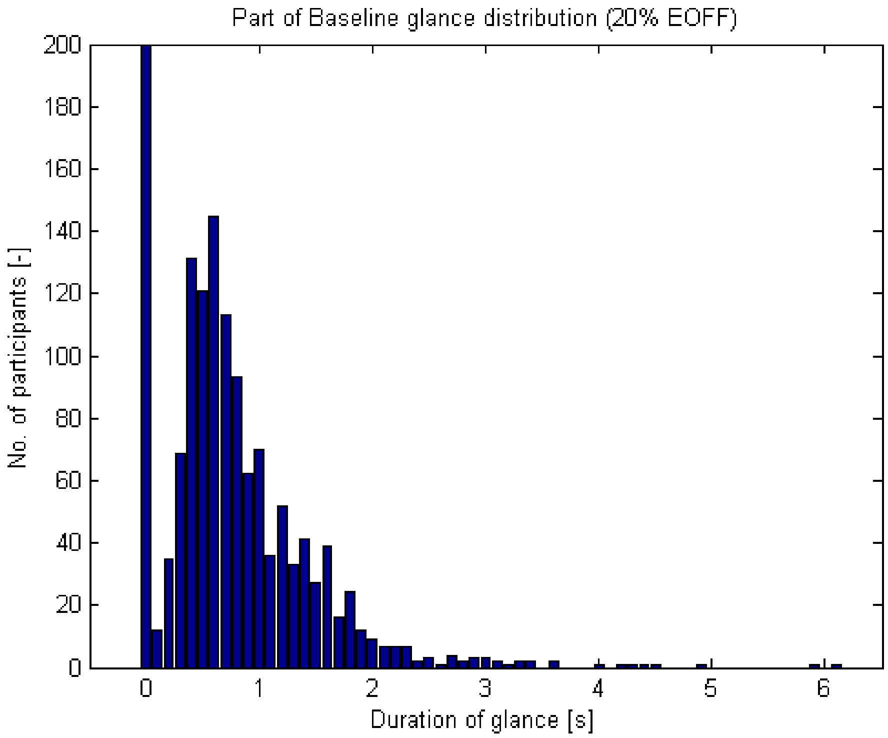

Figure A.2: Close-up of Baseline glance distribution

In the 20% of drivers who had EOFF, the duration of 0.3s – 1.5s off road glances seem to be the highest. Rare cases of drivers having off road glances greater than 3 seconds can also be seen.

A.1.2 Rockwell Glance distribution

Figure A.3 shows the contents of the Rockwell glance distribution.

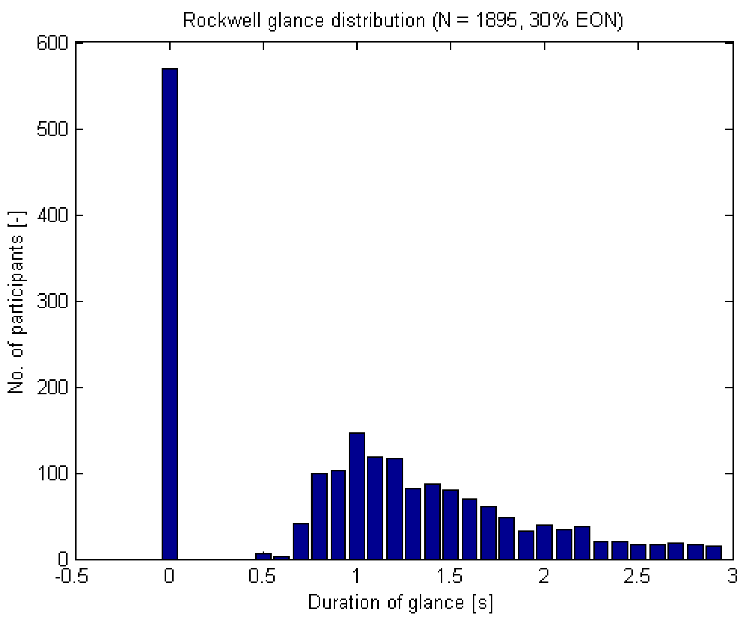

Figure A.3: Rockwell glance distribution

Since the Rockwell distribution was considered to be an important reference task by organizations such as NHTSA, the Rockwell distribution is assumed to represent eyes off road behaviour for different secondary tasks (Bärgman et al., 2015).

The Rockwell distribution had 30% of the participants keeping their eyes on the road. The rest of the participants tuned the radio for around 1s to 1.5s with the maximum being 2.9 seconds.

A.2 Reaction time distribution

The reaction time distribution was created in MATLAB based on the findings of Markkula et al. (2016) where they collected and analysed data from the SHRP2 and ANNEXT datasets. A greater understanding can be attained if 'Figure 4' is referred from Markkula et al.'s (2016) research. They use a term called 'Time from ELG to brake onset' which is synonymous with brake reaction time (the authors chose to use this term as they deemed it to be more accurate than Brake reaction time). ELG means End of Last off-road Glance. They also make use of inverse Tau $(\tau)^{-1}$ which is the optical equivalent of inverse Time To Collision (TTC^{-1}). From the data which consisted of car crashes and truck/bus crashes, a mean reaction time of 0.5 s was observed in Markkula et al.'s (2016) work. This was the basis for creating the reaction time distribution as mentioned earlier in Section 4.3.2.

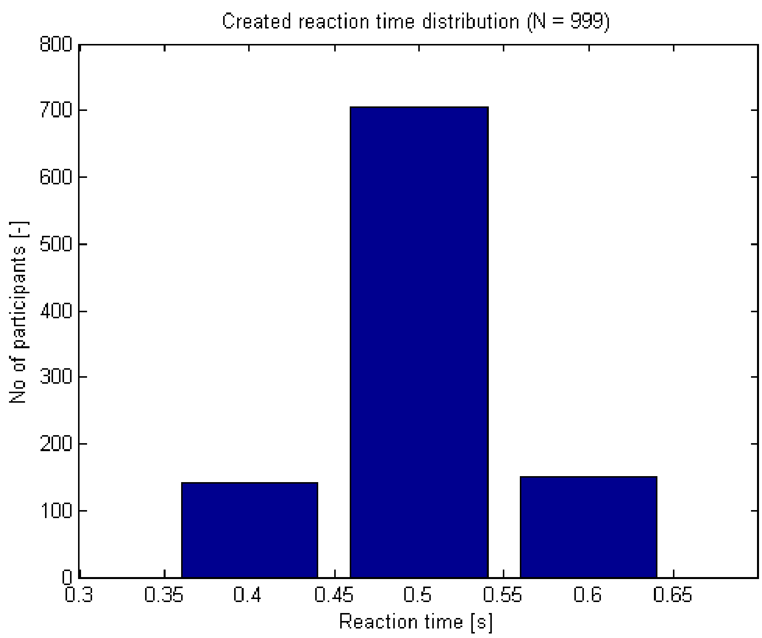

Figure A.4: Created Reaction time distribution

A normal distribution with a mean of 0.5 and standard deviation of 0.05 with a sample size of 1000 was created using the 'normrnd' function in MATLAB. A vector named 'binranges' was defined; and using the 'histc' function, the bin counts were obtained. Once bin counts were obtained, a classification was defined for simple representation in a bar chart. A bin range of 0.35 s to 0.45 s was considered to be a bin of 0.4 s, 0.46 s to 0.55 s was considered to be a bin of 0.5 s and 0.56 s to 0.65 s was taken to be a bin of 0.6 s. The total counts in the classified bins were 999. One count was excluded because it fell outside the defined bin ranges. Figure A.4 shows the created reaction time distribution.

Appendix B Counterfactual event table

Table B.1 shows one batch of simulations of Case 16 (Case 2014-76-003) for Baseline glances. The Weighted Crash/No crash metric is the product of the joint probability and the corresponding Crash metric. Similarly, the weighted impact speed is the product of the joint probability and the corresponding impact speed. The summation of the weighted Crash/No crash metric multiplied by 100 gives the percentage crashes for the particular case. Similarly, the summation of the weighted impact speeds gives a single value of impact speed for the aforementioned case.

Table B.1: Event table representing counter-factual events of Case 16

Event No. [-]	Glance duration [s]	Reaction time [s]	Deceleration [m/s2]	Crash/ No Crash [-]	Impact speed [m/s]	Joint probability [-]	Weighted Crash/No Crash [-]	Weighted Impact speed [m/s]
1	0	0.4	-6	0	0	0.113770646	0	0
2	0	0.5	-6	0	0	0.564847224	0	0
3	0	0.6	-6	0	0	0.121782664	0	0
4	0.1	0.4	-6	0	0	0.000284664	0	0
5	0.1	0.5	-6	0	0	0.001413296	0	0
6	0.1	0.6	-6	0	0	0.000304711	0	0
7	0.2	0.4	-6	0	0	0.00083027	0	0
8	0.2	0.5	-6	0	0	0.004122113	0	0
9	0.2	0.6	-6	0	0	0.000888739	0	0
10	0.3	0.4	-6	0	0	0.001636817	0	0
11	0.3	0.5	-6	0	0	0.008126451	0	0
12	0.3	0.6	-6	0	0	0.001752086	0	0
13	0.4	0.4	-6	0	0	0.00310758	0	0
14	0.4	0.5	-6	0	0	0.015428479	0	0
15	0.4	0.6	-6	0	0	0.003326424	0	0
16	0.5	0.4	-6	0	0	0.00287036	0	0
17	0.5	0.5	-6	0	0	0.014250733	0	0
18	0.5	0.6	-6	0	0	0.003072498	0	0
19	0.6	0.4	-6	0	0	0.003439688	0	0
20	0.6	0.5	-6	0	0	0.017077324	0	0
21	0.6	0.6	-6	0	0	0.00368192	0	0
22	0.7	0.4	-6	0	0	0.002680584	0	0
23	0.7	0.5	-6	0	0	0.01330	0	0

						8536		
24	0.7	0.6	-6	0	0	0.00286 9358	0	0
25	0.8	0.4	-6	0	0	0.00220 6145	0	0
26	0.8	0.5	-6	0	0	0.01095 3042	0	0
27	0.8	0.6	-6	0	0	0.00236 1507	0	0
28	0.9	0.4	-6	0	0	0.00147 0763	0	0
29	0.9	0.5	-6	0	0	0.00730 2028	0	0
30	0.9	0.6	-6	0	0	0.00157 4338	0	0
31	1	0.4	-6	0	0	0.00166 0539	0	0
32	1	0.5	-6	0	0	0.00824 4226	0	0
33	1	0.6	-6	0	0	0.00177 7478	0	0
34	1.1	0.4	-6	0	0	0.00085 3992	0	0
35	1.1	0.5	-6	0	0	0.00423 9887	0	0
36	1.1	0.6	-6	0	0	0.00091 4132	0	0
37	1.2	0.4	-6	0	0	0.00123 3543	0	0
38	1.2	0.5	-6	0	0	0.00612 4282	0	0
39	1.2	0.6	-6	0	0	0.00132 0413	0	0
40	1.3	0.4	-6	0	0	0.00078 2826	0	0
41	1.3	0.5	-6	0	0	0.00388 6563	0	0
42	1.3	0.6	-6	0	0	0.00083 7954	0	0
43	1.4	0.4	-6	0	0	0.00097 2601	0	0
44	1.4	0.5	-6	0	0	0.00482 8761	0	0
45	1.4	0.6	-6	0	0	0.00104 1094	0	0
46	1.5	0.4	-6	0	0	0.00064 0494	0	0
47	1.5	0.5	-6	0	0	0.00317 9916	0	0
48	1.5	0.6	-6	1	0.8264	0.00068 5599	0.0006856	0.000566 6
49	1.6	0.4	-6	0	0	0.00092 5157	0	0
50	1.6	0.5	-6	1	0.8264	0.00459 3211	0.0045932	0.003795 8

51	1.6	0.6	-6	1	4.3664	0.000990309	0.0009903	0.0043241
52	1.7	0.4	-6	1	0.8264	0.000379552	0.0003796	0.0003137
53	1.7	0.5	-6	1	4.3664	0.001884394	0.0018844	0.008228
54	1.7	0.6	-6	1	6.1664	0.000406281	0.0004063	0.0025053
55	1.8	0.4	-6	1	4.3664	0.000569328	0.0005693	0.0024859
56	1.8	0.5	-6	1	6.1664	0.002826592	0.0028266	0.0174299
57	1.8	0.6	-6	1	7.5464	0.000609421	0.0006094	0.0045989
58	1.9	0.4	-6	1	6.1664	0.000284664	0.0002847	0.0017554
59	1.9	0.5	-6	1	7.5464	0.001413296	0.0014133	0.0106653
60	1.9	0.6	-6	1	8.6864	0.000304711	0.0003047	0.0026468
61	2	0.4	-6	1	7.5464	0.000213498	0.0002135	0.0016111
62	2	0.5	-6	1	8.6864	0.001059972	0.00106	0.0092073
63	2	0.6	-6	1	9.7064	0.000228533	0.0002285	0.0022182
64	2.1	0.4	-6	1	8.6864	0.000166054	0.0001661	0.0014424
65	2.1	0.5	-6	1	9.7064	0.000824423	0.0008244	0.0080022
66	2.1	0.6	-6	1	10.6064	0.000177748	0.0001777	0.0018853
67	2.2	0.4	-6	1	9.7064	0.000166054	0.0001661	0.0016118
68	2.2	0.5	-6	1	10.6064	0.000824423	0.0008244	0.0087442
69	2.2	0.6	-6	1	11.4464	0.000177748	0.0001777	0.0020346
70	2.3	0.4	-6	1	10.6064	0.000166054	0.0001661	0.0017612
71	2.3	0.5	-6	1	11.4464	0.000824423	0.0008244	0.0094367
72	2.3	0.6	-6	1	12.2264	0.000177748	0.0001777	0.0021732
73	2.4	0.4	-6	1	11.4464	4.74E-05	4.74E-05	0.0005431
74	2.4	0.5	-6	1	12.2264	0.000235549	0.0002355	0.0028799
75	2.4	0.6	-6	1	13.0064	5.08E-05	5.08E-05	0.0006605
76	2.5	0.4	-6	1	12.2264	7.12E-05	7.12E-05	0.0008701
77	2.5	0.5	-6	1	13.0064	0.000353324	0.0003533	0.0045955
78	2.5	0.6	-6	1	13.7264	7.62E-	7.62E-05	0.001045

						05		6
79	2.6	0.4	-6	1	13.0064	2.37E-05	2.37E-05	0.0003085
80	2.6	0.5	-6	1	13.7264	0.000117775	0.0001178	0.0016166
81	2.6	0.6	-6	1	14.3864	2.54E-05	2.54E-05	0.0003653
82	2.7	0.4	-6	1	13.7264	9.49E-05	9.49E-05	0.0013025
83	2.7	0.5	-6	1	14.3864	0.000471099	0.0004711	0.0067774
84	2.7	0.6	-6	1	14.9864	0.00010157	0.0001016	0.0015222
85	2.8	0.4	-6	1	14.3864	4.74E-05	4.74E-05	0.0006825
86	2.8	0.5	-6	1	14.9864	0.000235549	0.0002355	0.00353
87	2.8	0.6	-6	1	15.6464	5.08E-05	5.08E-05	0.0007946
88	2.9	0.4	-6	1	14.9864	7.12E-05	7.12E-05	0.0010665
89	2.9	0.5	-6	1	15.6464	0.000353324	0.0003533	0.0055282
90	2.9	0.6	-6	1	15.6464	7.62E-05	7.62E-05	0.0011919
91	3	0.4	-6	1	15.6464	7.12E-05	7.12E-05	0.0011135
92	3	0.5	-6	1	15.6464	0.000353324	0.0003533	0.0055282
93	3	0.6	-6	1	15.6464	7.62E-05	7.62E-05	0.0011919
94	3.1	0.4	-6	1	15.6464	4.74E-05	4.74E-05	0.0007423
95	3.1	0.5	-6	1	15.6464	0.000235549	0.0002355	0.0036855
96	3.1	0.6	-6	1	15.6464	5.08E-05	5.08E-05	0.0007946
97	3.2	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
98	3.2	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
99	3.2	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973
100	3.3	0.4	-6	1	15.6464	4.74E-05	4.74E-05	0.0007423
101	3.3	0.5	-6	1	15.6464	0.000235549	0.0002355	0.0036855
102	3.3	0.6	-6	1	15.6464	5.08E-05	5.08E-05	0.0007946
103	3.4	0.4	-6	1	15.6464	4.74E-05	4.74E-05	0.0007423
104	3.4	0.5	-6	1	15.6464	0.000235549	0.0002355	0.0036855
105	3.4	0.6	-6	1	15.6464	5.08E-05	5.08E-05	0.0007946

106	3.5	0.4	-6	1	15.6464	0	0	0
107	3.5	0.5	-6	1	15.6464	0	0	0
108	3.5	0.6	-6	1	15.6464	0	0	0
109	3.6	0.4	-6	1	15.6464	4.74E-05	4.74E-05	0.0007423
110	3.6	0.5	-6	1	15.6464	0.000235549	0.0002355	0.0036855
111	3.6	0.6	-6	1	15.6464	5.08E-05	5.08E-05	0.0007946
112	3.7	0.4	-6	1	15.6464	0	0	0
113	3.7	0.5	-6	1	15.6464	0	0	0
114	3.7	0.6	-6	1	15.6464	0	0	0
115	3.8	0.4	-6	1	15.6464	0	0	0
116	3.8	0.5	-6	1	15.6464	0	0	0
117	3.8	0.6	-6	1	15.6464	0	0	0
118	3.9	0.4	-6	1	15.6464	0	0	0
119	3.9	0.5	-6	1	15.6464	0	0	0
120	3.9	0.6	-6	1	15.6464	0	0	0
121	4	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
122	4	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
123	4	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973
124	4.1	0.4	-6	1	15.6464	0	0	0
125	4.1	0.5	-6	1	15.6464	0	0	0
126	4.1	0.6	-6	1	15.6464	0	0	0
127	4.2	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
128	4.2	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
129	4.2	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973
130	4.3	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
131	4.3	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
132	4.3	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973
133	4.4	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
134	4.4	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
135	4.4	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973
136	4.5	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
137	4.5	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
138	4.5	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973
139	4.6	0.4	-6	1	15.6464	0	0	0

140	4.6	0.5	-6	1	15.6464	0	0	0
141	4.6	0.6	-6	1	15.6464	0	0	0
142	4.7	0.4	-6	1	15.6464	0	0	0
143	4.7	0.5	-6	1	15.6464	0	0	0
144	4.7	0.6	-6	1	15.6464	0	0	0
145	4.8	0.4	-6	1	15.6464	0	0	0
146	4.8	0.5	-6	1	15.6464	0	0	0
147	4.8	0.6	-6	1	15.6464	0	0	0
148	4.9	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
149	4.9	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
150	4.9	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973
151	5	0.4	-6	1	15.6464	0	0	0
152	5	0.5	-6	1	15.6464	0	0	0
153	5	0.6	-6	1	15.6464	0	0	0
154	5.1	0.4	-6	1	15.6464	0	0	0
155	5.1	0.5	-6	1	15.6464	0	0	0
156	5.1	0.6	-6	1	15.6464	0	0	0
157	5.2	0.4	-6	1	15.6464	0	0	0
158	5.2	0.5	-6	1	15.6464	0	0	0
159	5.2	0.6	-6	1	15.6464	0	0	0
160	5.3	0.4	-6	1	15.6464	0	0	0
161	5.3	0.5	-6	1	15.6464	0	0	0
162	5.3	0.6	-6	1	15.6464	0	0	0
163	5.4	0.4	-6	1	15.6464	0	0	0
164	5.4	0.5	-6	1	15.6464	0	0	0
165	5.4	0.6	-6	1	15.6464	0	0	0
166	5.5	0.4	-6	1	15.6464	0	0	0
167	5.5	0.5	-6	1	15.6464	0	0	0
168	5.5	0.6	-6	1	15.6464	0	0	0
169	5.6	0.4	-6	1	15.6464	0	0	0
170	5.6	0.5	-6	1	15.6464	0	0	0
171	5.6	0.6	-6	1	15.6464	0	0	0
172	5.7	0.4	-6	1	15.6464	0	0	0
173	5.7	0.5	-6	1	15.6464	0	0	0
174	5.7	0.6	-6	1	15.6464	0	0	0
175	5.8	0.4	-6	1	15.6464	0	0	0
176	5.8	0.5	-6	1	15.6464	0	0	0
177	5.8	0.6	-6	1	15.6464	0	0	0
178	5.9	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
179	5.9	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
180	5.9	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973

181	6	0.4	-6	1	15.6464	0	0	0
182	6	0.5	-6	1	15.6464	0	0	0
183	6	0.6	-6	1	15.6464	0	0	0
184	6.1	0.4	-6	1	15.6464	2.37E-05	2.37E-05	0.0003712
185	6.1	0.5	-6	1	15.6464	0.000117775	0.0001178	0.0018427
186	6.1	0.6	-6	1	15.6464	2.54E-05	2.54E-05	0.0003973
						Sum = 1	Sum = 0.025	Sum = 0.19