



The Analysis of Injury Mechanisms from Frontal Car Accidents

-Prediction of Injuries from Event Data Recorders and Intrusion Data

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**Faculty of Industrial Engineering, Mechanical
Engineering and Computer Science
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Edda Doris Þráinsdóttir

30 ECTS thesis submitted in partial fulfillment of a
Magister Scientiarum degree in Industrial Engineering

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Abstract

Significant developments have been made in the understanding of passenger car collisions over the recent decades through research from real life accidents and with dummies. However, there is limited understanding of how crashes occur in real life and further knowledge is required to understand injury risk in real world scenarios. Analysis of real-world crashes increases the ability to obtain such knowledge. This study aims to understand injury severity for the car's occupant in frontal car crashes. In this project, real world data, containing frontal collisions was used to estimate how the velocity change (ΔV), the vehicle body intrusion and the occupant load criterion (OLC) affected the occupant's injury. Multiple logistic regression analysis was used to evaluate the relationship between injury severity, ΔV , OLC and intrusion.

In total 268 cases were analyzed. A regression analysis of the data provided a statistically significant relationship (95% CI) between injury, OLC and ΔV . The estimate for intrusion was not statistically significant but was more influential on the injury prediction. The study concluded that the OLC is a stronger predictor for severe injuries where ΔV is a more reliable predictor for minor injuries. As expected, cases with intrusion had higher ΔV on average, than those without intrusion. The risk of receiving MAIS2+ injuries and MAIS3+ injuries increases with higher ΔV , with a higher OLC and with a greater intrusion.

Keywords: AIS, frontal impact, intrusion, National Automotive Sampling System, Occupant Load Criterion, ΔV .

Útdráttur

Veruleg þróun hefur orðið í rannsóknum umferðarslysa á undanförunum áratugum með það að leiðarljósi að tryggja öryggi farþega. Með hjálp hermibreyta og út frá rannsóknum á gögnum fengnum úr raunverulegum árkestrum er skilningur vísindamanna á hegðun árekstra fólksbifreiða og þeim áverkum sem farþegar hljóta úr þeim sífellt að aukast. Frekari þekking er nauðsynleg til að skilja áhættuþætti og líkur á áverkum meðal farþega í bílslysi. Þetta verkefni miðar að því skoða framárekstra og greina þá áverka sem farþeginn hlaut. Skoðuð var hraðabreytingin (ΔV) sem bifreiðin varð fyrir við árkesturinn. Þeir áverkar sem farþeginn hlaut voru metnir og reynt að finna hver megin orsök þeirra væri. Innbyrðis formbreyting á farþegarými bílsins var einnig skoðuð og metið hvort áverkana mætti rekja til innbyrðis formbreytinga á innra rými bílsins og hvernig hraðabreytingin hafði áhrif á innbyrðis formbreytingu farþegarýmisins.

Með fjölþátta lógistískri aðhvarfsgreiningu voru tengsl á milli áverka, formbreytinga á farþegarými bílsins, hraðabreytingin (ΔV) og höggið sem myndaðist við áreksturinn á farþegann (OLC) skoðuð. Í heildina voru 268 farþegar skoðaðir. Tölfræðileg marktækni með 95 % öryggisbili sýndi að ΔV , OLC og áverkarnir sýndu marktækni en formbreyting á innra rými bílsins var ómarktæk. Rannsóknin leiddi í ljós að OLC hefur sterkara forspárgildi fyrir minniháttar meiðsl á meðan ΔV var sterkara fyrir alvarlegri áverka. Slyss með innbyrðis formbreytingum höfðu einnig hærra ΔV samanborið við árekstra þar sem engin formbreyting átti sér stað. Niðurstöður rannsóknarinnar sýndu að formbreyting á farþegarými bílsins greindist við hærra ΔV , við hærra OLC og aukin formbreytingu á innra rými bílsins eykur áhættuna á MAIS2+ og MAIS3+ áverkum samkvæmt þeim gögnum sem stuðst var við í þessari rannsókn.

Preface

This report is the result of my master thesis work carried out at Chalmers (Vehicle Safety Division), in collaboration with Volvo Group Trucks Technology (GTT), Gothenburg. The project required working with three different organizations', Chalmers, Volvo, and Virginia Tech Univeristy. This thesis fulfills partial requirement for the Master of Science degree in Industrial Engineering. This thesis work was started in January 2016 and finished in January 2017.

Table of Contents

List of Figures	x
List of Tables.....	xii
Abbreviations.....	xiii
Acknowledgements	xv
1 Introduction and Literature Review.....	1
1.1 Research Goal and Questions	2
1.2 Scope and Limitations of the Study	3
2 Methods and Relevant Literature Review.....	5
2.1 Choice of Methods.....	5
2.2 Abbreviated Injury Scale	6
2.3 Crash Severity.....	7
2.4 Safety Design of the Vehicle	8
2.5 Real Data Source	9
2.6 The Velocity Change of ΔV Based on EDR.....	10
2.6.1 Event Data Recorders	11
2.7 Occupant Load Criterion	13
2.8 Statistical Analysis and Computational Statistics.....	15
2.8.1 Binary Logistic regression	15
2.8.2 Injury Risk Curve.....	16
3 Data Analysis and Results.....	17
3.1 Descriptive Statistics	17
3.1.1 Descriptive Statistics for Variables	17
3.1.2 Descriptive Statistics for Injury Biomechanics	21
3.2 Logistic Regression Models with Intrusion as a Binary Numbers	22
3.3 MAIS Logistic Regression Models for Head and Chest	25
3.4 Logistic Regression Models with Intrusion as a Categorical Variable.....	27
4 Discussion	33
5 Conclusions.....	37
References	39
Appendix A.....	46
A.1.1 Example R Code	46
A.1.2 Output From R	48
A.1.3 OLC Calculation With Matlab.....	48
A.1.4 MAIS Distribution for Each Year.....	51
A.1.6 MAIS3+ and Chest Injury.....	52

List of Figures

Figure 1.1	Definition of the NASS/CDS crash angle.....	4
Figure 2.1	The pretension's role is to remove some of the slack between the occupant and the belt by pulling the seat belt webbing back (Untaroiu, et al. 2012).	9
Figure 2.2	Measurement of ΔV from EDR recording during impact. Retrieved from Event data recorders.	11
Figure 2.3	2007 model of Lexus after impact with Cadillac Eldorado 2002 model on the left picture and its EDR recorded ΔV on the right figure. Retrieved from http://www-nass.nhtsa.dot.gov/nass/cds/SearchForm.aspx , NASS case # 2012-043-194.	12
Figure 2.4	Three categories of EDR pulse recording (Iraeus & Lindquist, 2014).	12
Figure 2.5	Single mass model used for calculation of the OLC (Lefer & Reboloso, 2012).	13
Figure 2.6.	Calculations of OLC with acceleration, velocity and the displacement of the vehicle (blue curve) and the calculated equivalent for the occupant (red curve). OLC was used to assess passenger car acceleration (Lefer & Reboloso, 2012).	14
Figure 2.7	The restraint spring force (Lefer & Reboloso, 2012).	14
Figure 3.1	Longitudinal ΔV distribution with a circle around the peaks in the distribution. The red line represents intrusion and the blue line represents cases without intrusion.	34
Figure 3.2	The OLC distribution with a circle around the peaks in the distribution. The red line represents intrusion and the blue line represents cases without intrusion.	20
Figure 3.3	The correlation between estimated OLC and the ΔV	35
Figure 3.4	MAIS2+ Injury risk curves with 95% confidence intervals for accident containing OLC 5 and OLC 20. The injury risk curve is plotted versus the longitudinal ΔV : Intrusion (left) and no intrusion (right).	23
Figure 3.5	MAIS3+ Injury risk curves with 95% confidence intervals for accident with OLC 5 and OLC 20: The injury risk curve is plotted versus the longitudinal ΔV : intrusion (left) and no intrusion (right).	39
Figure 3.6	Injury risk curves with 95% confidence intervals estimated for the chest. The injury risk curve is plotted versus the longitudinal ΔV : Intrusion (left) and no intrusion (right).	41

Figure 3.7 Frequency of accidents with intrusion severity for fully recorded time history. The frequency is presented on the y-axis and the intrusion level on the x-axis.....	43
Figure 3.8 Injury risk curves with 95% confidence intervals estimated for the intrusion severity from 0-5. The injury severity is presented on the y-axis. The injury risk curve is plotted versus the longitudinal ΔV	30

List of Tables

Table 2.1 Abbreviated Injury Scale.....	6
Table 3.1 Mean ΔV , the range and the standard deviation for ΔV above and g below.	18
Table 3.2 MAIS frequency for accidents without intrusion.....	33
Table 3.3 MAIS frequency for accidents with intrusion.....	19
Table 3.4 MAIS Injuries for each body region from accidents with intrusion.	36
Table 3.5 MAIS Injuries from accidents without intrusion	22
Table 3.6 Regression model for prediction of the risk of MAIS2+ for accident with and without intrusion. This table includes the intercept of the dependent variables above and dependent variable below.	38
Table 3.7 Regression model for prediction of the risk of MAIS3+ in accidents with intrusion and fully recorded time history for the velocity change. This table includes the intercept of the dependent variables.	25
Table 3.8 Regression model for prediction of the risk of AIS2+ for chest injuries in accidents with intrusion and fully recorded time history for the velocity change. This table includes the intercept of the dependent variable and the independent.....	26
Table 3.9 The six categories for the intrusion severity.	42
Table 3.10 Risk of MAIS2+ injuries at a certain level of intrusion when ΔV is 40 km/h and OLC is 5g and 20g.....	43
Table 3.11 Regression model for prediction of the risk of intrusion severity versus ΔV for fully recorded time history. This table includes the intercept of the dependent variables.	31

Abbreviations

AIS	Abbreviated Injury Scale
BMI	Body Mass Index
CDS	Crashworthiness Data System
EDR	Event Data Recorders
Frontal Stiffness	The relation between force and displacement during the crush of frontal structures
MAIS	Maximum Abbreviated Injury Scale
MVCs	Motor Vehicle Crashes
NASS	U.S National Automotive Sampling System
NCSS	U.S National Crash Severity Study
NHTSA	U.S National Highway Traffic Safety Administration
OLC	Occupant Load Criterion

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1 Introduction and Literature Review

Traffic safety and car accidents have become a major topic for automotive research during recent years. The number of road users worldwide is continuously increasing, making the severe injury and mortality of people from car accidents a primary concern. Through research and development in vehicle safety, improvements have decreased the frequency of casualties and death in motor vehicle crashes (MVCs). However, they are still one of the leading causes of hospitalization and death (Weaver et al., 2015). World wide more than a million fatalities are caused by road traffic and affects more than 1.24 million people annually. Globally, road traffic injuries are estimated to be the eighth leading cause of death (World Health Organization (WHO), 2014). Investigation and statistical analysis in the United States indicates that more than 5.3 million police reported vehicle crashes occur annually, resulting in 32,000 fatalities and over 2,200,000 injured victims (Stigson, Kullgren, & Rosen, 2012).. The successful design of a road safety transport system, including all safety technologies, requires an understanding of the whole chain of events in a car crash. Forces related to both the impact type and the speed influence the resulting injuries. Analysis of real world vehicle collisions enhances the understanding in this field and identifies how to improve the effectiveness of safety technology.

Statistics indicate that the severity of injuries caused as a result of frontal impact, has improved in recent years and is the most relevant impact regarding occupant's injury causation (Johannsen et al., 2013). Since head-on impact is often the result of these accidents, the closing velocity between the involved vehicles is usually larger than an accident with a side or rear impact (Wågström, et al., 2005). The European Commission's Seventh Framework Program, Project FIMCAR (Frontal Impact and Compatibility Assessment Research) indicates that approximately 40% of injuries with injury classified as MAIS2+ and 30% of fatal injuries suffered by occupants are involved in collision with more than 75% frontal overlap (FIMCAR, 2011). Frampton (2006) indicates a survival potential with the velocity change of less than 59 km/h for 49% of drivers and 60% of frontal seat passengers equipped with improved passive safety (Frampton, Page, & Thomas, 2006). In frontal collision such as small overlap and oblique crashes where the involved vehicle possesses poor structural engagement results in a high number of mortalities (Iraeus & Lindquist, 2014b).

In a frontal collision, intrusion can cause the vehicle's bodywork to deform into the occupant's compartment resulting in serious injuries. Therefore it is important to understand the influence of the intrusion and the obtained crash pulse severity on injury risk, independently of each other, by quantifying the crash severity for the car occupant from a vehicle frontal collision. To achieve a higher level of knowledge in that field, a better understanding of how the combination of acceleration and intrusion affects the type and severity of injuries to a car's occupants is needed (Gabauer, et al, 2004; Kullgren, 2008). The resulting injury from frontal impact, cannot only be caused by the crash severity with regards to acceleration but also because of the duration of the accident. Wykes et al (1998) studied the effect of the pulse duration and found that the duration of the pulse may influence the occupants' injury risk. His research indicates that the ride

down time for different deceleration pulses affects injury outcome. The length of the duration depends on the stiffness of the vehicle, the ride down distance and the vehicle's geometry. To estimate the passive safety level with security technology, crashes from real life scenario give the most accurate results (Ydenius, 2010).

Injury biomechanics uses the principles of mechanics to study the behavior of the biological material in real time as they are subjected to a dangerous condition, for example in traffic accidents. The ability to develop a less hazardous environment depends on our understanding of injury biomechanics. Biomechanics is the science that applies the principles of mechanics to biological systems. Injuries to the human body occur when anatomical structures are deformed beyond their failure limits, which result in damage to tissue or alterations to their normal functions (Wisman, Janssen & Beusenberg, 2000; Gabauer, et al, 2004; Kullgren, 2008).

The broad goal of injury biomechanics research is to understand the injury process and to develop ways to reduce or eliminate the structural and functional damage that can occur in an impact environment. To achieve this goal, researchers must identify and define the mechanisms of impact injury, transpose the responses of tissues and systems to a range of impact conditions. To determine the level of response at which the tissues or systems will fail to recover and consequently develop protective materials and structures that will reduce the dangerous levels of energy and force delivered to the body. To achieve this test devices and computer models are developed to respond to impacts in a human-like manner, so that protective systems can be accurately evaluated. A biomechanical tolerance limit is the maximum mechanical load a person can handle without getting injured and is different between individuals. The severity of the resulting injury is indicated by the expression injury severity and is defined as the magnitude of change, regarding physiological alterations or structural failure occurring to a living body as a consequence of mechanical violence. An injury scaling system is a numerical classification of the type and describes the severity of an injury (Wisman, et al., 2000). One commonly used is the Maximum Abbreviated Injury Scale (MAIS), which will be utilized in Chapter 2.2 (Haasper et al., 2010).

1.1 Research Goal and Questions

A One way, a car manufacturer, can affect the pulse of the accident, and hence, the peak acceleration is to change the characteristics of the energy absorbing parts of the vehicle body. The pulse of the crash of a given vehicle depends on the initial velocity, the collision object and the deformation mode of the engaged structures. In a severe frontal collision, most of the cars frontal structures are deformed to protect the passenger from injuries related to intrusion. Therefore, the car passenger compartment must withstand high forces, it is important to review the design of passenger cars constantly and investigate what steps should be taken towards reducing the number of road fatalities (Wågström, et al., 2004).

While research has shown that intrusion increases the risk of injury, there have been limited studies quantitatively describing the relationship between injury and crash severity indicators like velocity change (ΔV) and intrusion. The overall aims of the study outlined in this report are to analyze the relationship between the ΔV and the OLC . The OLC is

based on the resulting restrain force, which is applied to the occupant chest during the impact. The occupant injuries and the intrusion into the occupant compartment in a head-on collision will also be examined. The study aim to understand the influence of the intrusion and/or the pulse on the resulting impact severity independently of each other by quantifying the possible crash severity reduction for the car's occupant in frontal car crashes. The objective of the research is to provide injury risk curves for injuries in frontal crashes.

- The hypothesis is that the pulse depends on the stiffness of the car, and as a consequence affects the resulting deformation of the vehicle body during an impact.
- The hypothesis is also that the OLC may indicate how the resulting restrain force towards the occupant is influenced by intrusion.

The more specific questions were:

- How do the ΔV , the intrusion into the occupant compartment, the OLC and the deformation of the car's body affect the occupant's injury severity?
- Is there a correlation between the ΔV and the resulting OLC?

1.2 Scope and Limitations of the Study

The U.S. National Highway Traffic Safety Administration database (*Retrieved from <http://www-nass.nhtsa.dot.gov/nass/cds>*) was first searched to identify suitable cases for analysis. Suitable cases adhere to the following criteria.

- Airbag deployment.
- Fully recorded EDR velocity history.
- Available injury data for either the left or right front seat occupant.
- Belted occupants only.
- Comprised of a single impact only.
- A single frontal collision with no vehicle rollover or driver ejection and crash angle between +60 and -60 degrees.
- Vehicle model year 2003 or newer.
- Single and two-vehicle crashes.

Following data were excluded in this study:

- Multiple event crashes.
- Crashes with unknown injuries.
- Large vehicles and trucks.
- Crashes with ΔV recorded as 9999 (unknown).
- Crashes with incomplete time records.
- Intrusion in toe and floor pan.

To obtain a correct representation of the severity from the pulse of the accident, cases with incomplete records were excluded. In total, 656 cases needed to be excluded due to a not fully recorded ΔV time history. With this criteria applied, 268 crashes occurring between 2003 and 2014 were selected.

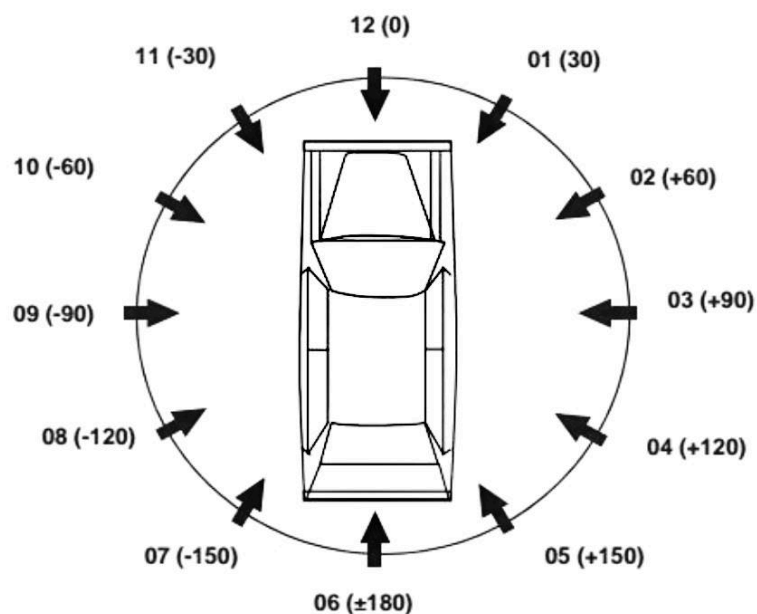


Figure 1.1 Definition of the NASS/CDS crash angle

2 Methods and Relevant Literature Review

This chapter will provide an overview of research methods utilized in this study and stipulate how the data used in the project was collected, identified, implemented and analyzed. To analyze the correlation between the crash severities, the intrusion and the injury outcome, data from real world accidents recorded by Event Data Recorders (EDR, an industry standard, installed by automakers) from 2003-2014 were analyzed. The velocity change (ΔV) which is the total change in vehicle velocity over the crash duration, the injury information, the intrusion severity and information regarding the vehicle were retrieved from the NASS database (*Retrieved from <http://www-nass.nhtsa.dot.gov/nass/cds>*) using the software Statistical Analysis Systems (SAS). The SAS files used in this study were retrieved from <ftp.nhtsa.dot.gov/NASS>.

To answer the research questions presented in Chapter 1.1 the following information was needed:

- Calculation of the Occupant Load Criterion (OLC), which estimates the occupant's mean acceleration.
- Probability relationship made with binary logistic regression for MAIS2+ and MAIS3+ for belted occupants in accidents, with and without intrusion, versus velocity change and OLC to estimate the risk of a specific injury severity for a specific severity of collision.
- The probability of deformation of the vehicle body at a specific ΔV and specific acceleration and compare the OLC and ΔV to estimate which parameter gives a significantly better result.

2.1 Choice of Methods

Binary logistic regression analysis is used to predict injury severity in single-impact frontal vehicle crashes, involving front seat occupants, equipped with frontal airbag deployment. Risk curves for MAIS2+ and MAIS3+, where MAIS is the dependent variable and intrusion, OLC and ΔV are the independent variables, were made to predict the relationship between MAIS, ΔV , intrusion and OLC.

As mentioned above, the NASS database is the only database containing EDR records of the ΔV during an impact. The information retrieved from the NASS database can be used to analyze the occupant injuries, the intrusion, the ΔV and the OLC in individual crashes. The anticipated result will be risk curves that estimates the probability relationship between injuries versus ΔV , intrusion and OLC.

The study is based on the analysis of frontal collisions extracted from Event Data Recorders (EDR) and downloaded from the National Accident Sampling System

Crashworthiness Data System, (NASS-CDS) and matched with detailed occupant injury information (Gabauer & Gabler, 2004). The Abbreviated Injury Scale (AIS), which describes the injury regarding its anatomical location, its relative severity and the type of injury scale, is widely used in biomechanics to evaluate and monitor injuries. The U.S NASS (National Accident Sampling System) utilizes hospital records to establish the occupant's injuries to calculate corresponding maximum AIS for each individual. The Matlab software was used to calculate the Occupant Load Criterion. By using the Matlab software, the numerical calculation is more flexible and easier to alter (Houcque, 2005; Park & Kan, 2010).

2.2 Abbreviated Injury Scale

Abbreviated Injury Scale (AIS) was developed in the 1960's by a group of 75 specialists from around the world and introduced in 1971 to aid vehicle crash investigators AAAM, 2001. Since then the scale has been revised six times (1976, 1980, 1985, 1990, 1998 and 2005). The AIS scale was developed by the Association for the Advancement of Automotive Medicine and is an injury coding system that gives the opportunity to analyse the injuries, according to their severity (AAAM, 2001; Wilson, Grandy & Hoyt, 2007).

The AIS, which describes the injury regarding its anatomical location, its relative severity and the type of injury scale, is widely used to evaluate and monitor injuries (Wisman, Janssen & Beusenberg, 2000). The scale is a severity scoring system that classifies an individual injury in each body region according to its relative importance on a six-point ordinal scale. Zero indicates no injury, one classifies a minor injury with a fatality rate of zero percent, two as moderate with the fatality rate of 0,1-0,4 percent, three is serious with the fatality rate of 0,8-2,1 percent, four is severe with the fatality rate of 7,9-10,6 and five is critical with the fatality rate of 55,1-58,4 percent. Six is the maximum number and indicates an untreatable injury with 100 percent probability of dying. Table 2.1 indicates the Abbreviated Injury Scale according to Association for the Advancement of Automotive Medicine 2001 (AAAM, 2001).

Table 2.1 Abbreviated Injury Scale.

AIS Score	Injury severity	Probability of death
1	Minor	0%
2	Moderate	1-2%
3	Serious	8-10 %
4	Severe	50-50%
5	Critical	50-50 %
6	Un survivable	100%

The limitation of the AIS code is that the scale does not represent a linear scale and the difference between the scores is not the same. The difference in score between AIS4 and AIS5 is not the same as for AIS1 and AIS2 (Stigson, Kullgren, & Rosen, 2012). The highest AIS score for a particular body part is used as a measure of the overall injury severity, identified as the MAIS (Maximum AIS) (Petrucelli et al., 1981). The Maximum Abbreviated Injury Score (MAIS) is frequently used for assessing overall severity and does not determine the effect of multiple injuries in the patient. MAIS2- indicates an occupant with non-serious group damage and MAIS 3+ represents an occupant with a severe injury. The AIS scale is based on the severity of the injury to the chest, the thorax, the abdomen and the head (AAAM, 2001; Tsoi & Gabler, 2015).

2.3 Crash Severity

The severity of injury is dependent on the inertial loading of the occupant related to the crash pulse and the occupant interaction with the restraint system. The other injury mechanism depends on the intrusion of the occupant compartment resulting from the crash impact. Intrusion is the deformation of the vehicle into the occupant's compartment. The intrusion can be classified into six groups and are indicated in table 3.9. For the last years, passenger car compartments have become stiffer to minimize the occupant compartment intrusion in severe accidents, especially for frontal accidents. Historical research has used crash data and hospital data to understand the relationship between injuries and intrusion derived from the US database, National Automotive Sampling System (NASS) (Stigson, et al., 2012; Wisman, et al., 2000).

The mass ratio in a car-to-car frontal collision has a significant impact on the involved vehicles as well as the weight of the striking car affects the opponent vehicle. A heavier striking car will result in higher injury risk for the opponent car (Adolph et al., 2015). Differences in the seriousness of damage or the acceleration, between two vehicles crashing into each other, can be significant. The occupant injuries from one vehicle can be severe, even resulting in a fatality, whilst the other survives with minor injuries. When aware of this significant difference, the crash incompatibility between the vehicles involved is identified and defined as inefficient energy absorption. When a passenger car collides front on a heavier car, or object, the lighter car receives higher deceleration causing higher pulse on the passenger during the deceleration of the lighter car. The mass of the object that the vehicle collides with can be the largest factor causing aggressiveness in real world crashes (Evans, 1994; Thomas & Frampton, 1999).

Many belted occupants receive severe injuries without a great level of passenger compartment intrusion, which indicates that the injury mechanism is related to the crash pulse and the occupant interaction towards the restraint system (Wågström et al., 2013; FIMCAR, 2011). Pulses from real world frontal car accidents indicate a correlation between acceleration levels and injury risk. The risk of long-term injury increases significantly when the vehicle rapidly decelerates at the point of impact (Johannsen et al., 2013). Frontal impacts with compartment intrusion can lead to serious injuries where the intrusion can cause a deformation of the car body into the occupant compartment (intrusion) (Wågström, et al, 2013). Because of the impact, the occupant moves forward until the belt resulting in possible contact with the forward moving occupant and

backward-retreating instrument panel or steering wheel restrains him. When a vehicle obtains extensive body deformation the risk of passenger's injury occurring from a collision with the inner body of the car increases (Nakamura, Hashimoto, & Yasue, 1993).

Several factors affect the severity of the force that the individual is subjected to during a crash. The strongest factor would be the relative velocity between the two impacting vehicles or vehicle and object, their mass and their structure as well as the angle of impact (Stigson, et al. 2012; Correia, et al. 2001). Comparing a given intrusion classified into six groups dependent on their severity, from the NASS data, the occupant injuries and ΔV can highlight the relationship between the ΔV , the intrusion, the crash pulse and the occupant's injury cause.

2.4 Safety Design of the Vehicle

The design and development of the vehicle structure to incorporate occupant protective system and efforts to increase the crashworthiness have proven to be significantly advantageous. The restraint system, with three-point safety belts and the airbag, were significant successes in the development of the car's protective system. This equipment has been shown to prevent injuries during a crash. The safety of the occupant within the vehicle depends on the performance of the car's structure and the occupant's restraint system. The vehicle's role in crash protection is to absorb the energy of the accident efficiently and protect the integrity of the occupant compartment. The vehicle's structural performance is described as the occupant compartment intrusion along with the vehicle's crash pulse (Park & Kan, 2010). The seat belt or safety belt is the vehicle's most critical safety equipment (Untaroiu et al. 2012). The use of a three-point seat belt is estimated to reduce the probability of death or serious injuries by 45% or 60% respectively (Kahane, 2000). The fundamental role of the seatbelt is to maintain the passenger in the interior of the vehicle by tightening in the event of a collision, thus holding the occupant in place. During a collision, the belt will apply most of the stopping force towards the rib cage and the pelvis (Cristian & Catalina, 2009). In the early stages of a collision, the safety belt is exclusively responsible for the restraint of the occupant.

The restraint system consists of a safety belt with pretension, a load limitation and an airbag. Pretension and load limiters are designed to make the seat belt work more effectively. The pretensioners remove some of the excess slack between the occupant and the belt almost instantly when sensing impact by pulling the seat belt webbing back. Load limiters allow the belt to extend when forces on the belt rise above a certain predetermined level. Figure 2.1 indicates the pretensioners role (Kahane, 2013). The effect of the safety belt system is divided into two phases. In the first phase, the belt pretensions, creating the optimum pre-requisites for the restraint of the occupant for the first few milliseconds. The second phase, which is the load limitation during the forward displacement, maintains the force through the shoulder belt on the occupant to a pre-defined level, leading to an optimum utilization of the space available in the interior (Zellmer, et al. 2001).



Figure 2.1 The pretension's role is to remove some of the slack between the occupant and the belt by pulling the seat belt webbing back (Untaroiu, et al. 2012).

Nowadays, vehicles are equipped with sensors, which can provide information such as information regarding the brakes, the vehicle's acceleration, the velocity and the time history of the ΔV , the distances between itself and other vehicles or obstacles, night vision, usage of belts and other forms of data. The ΔV and the time history of the restraint system during the crash can give a clue of how the occupant's movement during the collision behave and how to improve further the vehicle's safety performance (Cristian & Catalina, 2009; Untaroiu, et al. 2012; Krusper, 2014).

2.5 Data Sources

Car accidents sampling and investigation teams operate worldwide for a better knowledge and understanding in the automotive research field as well as for safety developments. The National Accident Sampling System (NASS) collects accidents in the USA while Crash Injury Research and Engineering Network (CIREN) works in the US and Germany In-Depth Accident Study (GIDAS) in Germany. GIDAS provides accident and injury data from real world traffic accidents which are presented annually. The research teams consist of technical and medical students who investigate the accident scene and the data in the hospitals. GIDAS started in 1999 and is a joint project of the Federal Highway Research Institute (BAST) and the German Association for Research in Automobile Technology (FAT). Approximately 2,000 accidents are recorded annually providing information of all kinds of traffic participants (Pfeiffer, 2006), such as information about the environment (meteorological influences, street condition, traffic control), the vehicle (deformations, technical characteristics, safety measures), the occupant (first aid measures, therapy, rehabilitation) and the injury (severity, description, causation).

In January 1977, National Crash Severity Study (NCSS) and National Automotive sampling system (NASS) were established in the U.S and began to sample data from car accidents to help researchers to analyze motor-vehicle crashes and the resulting injuries. In 1980, NCSS published a summary with data from accidents including the ΔV , fatalities,

injuries and risk of injury or fatalities for various crash modes. NASS is operated by the National Highway Traffic Safety Administration (NHTSA) which is part of the U.S. Department of Transportation. NASS is divided into two parts: the Crashworthiness Data System (CDS) and the General Estimates System (GES). Their data collection began in 1979 in 10 geographic sites, called Primary Sampling Units (PSU's). The database is the largest in the world and most frequently used for research purposes since it is publically available (Johnson & Gabler, 2014).

The CDS NASS files contains information about the accident, photographs from the crash sites, and evidence such as skid marks, fluid spills, broken glass, and bent guardrails. Personal information regarding the car's occupants such as names, addresses, license and registration numbers, and even specific crash locations are not included in public NASS files. GES has collected data on approximately 60,000 crashes each year since 1979. They collect data from a nationally representative sample of police reports on all types of accidents from minor to severe. The reports, which are chosen from 60 areas, indicate the geography, roadway mileage, population and traffic density of the U.S. Their information are useful to estimate the amount of different kinds of motor vehicle crashes and their effect. NASS collects the data from event data recorders (EDR) in conjunction with National Automotive Sampling System/Crashworthiness Data System (NASS-CDS; Gabauer & Gabler, 2006; NASS).

2.6 The Velocity Change of ΔV Based on EDR

Velocity change (ΔV) is the total change in vehicle velocity over the crash duration and can be seen in Figure 2.2. The velocity change is a common measure of crash severity and can be used to predict consequential passenger injuries in the collision, to make injury risk curves and to estimate the occupant's injury risk during the car crash from factors such as the vehicle itself, the crash, and the occupant (Gabauer & Gabler, 2006; Grant et al., 2007; Weaver et al., 2015). Estimations on the crash protection safety features require a measurement for quantifying impact severity. The ΔV is the primary descriptor of collision severity used in most real-live crash databases. However, one of ΔV limitations is that it does not account for the time over which the crash pulse occurs (German, et al. 2007).

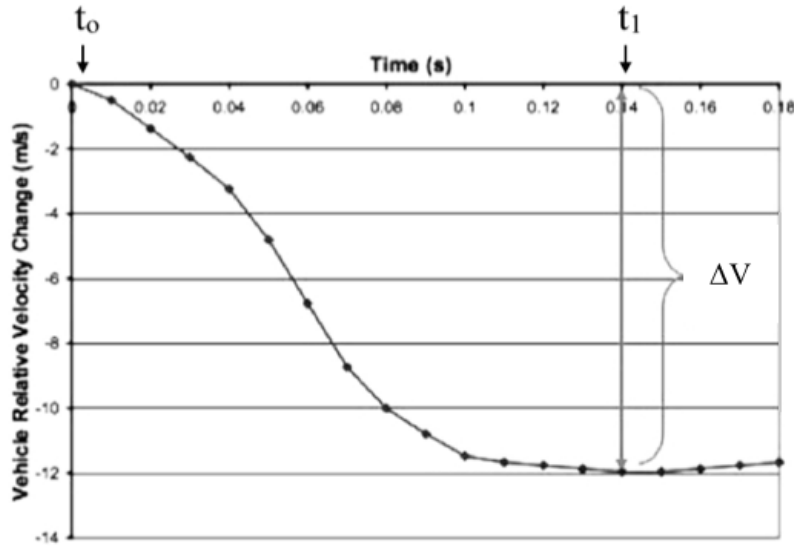


Figure 2.2 Measurement of ΔV from EDR recording during impact. Retrieved from Event data recorders.

$$\Delta V = V_{t1} - V_{t0} \quad (2.1)$$

$$a = \frac{V_{t1} - V_{t0}}{t1 - t0} \quad (2.2)$$

Figure 2.2 indicates the ΔV which is described as the longstanding metric for crash severity and is defined as the total change in vehicle velocity over the duration of a crash event from t_0 to t_1 . ΔV is calculated as the Equation 2.1 above indicates (Park & Khan, 2010) where t_1 is the final time and t_0 is the start time. The crash pulse however is the continuous acceleration recorded over time and is calculated according to Equation 2.2 (Iraeus & Lindquist, 2014).

2.6.1 Event Data Recorders

Event Data Recorders (EDR's) are an industry standard, installed by automakers to give them the opportunity for independent assessment of crash severity. NASS collects the data records from EDR's to conduct further investigations into the conditions of the vehicle crashes. Today, NASS and GIDAS are the only databases containing information on ΔV , calculated when the impact occurs. While Gidas contains estimations of ΔV for the crash reconstructionists NASS is the only databases consisting of real world data from the Event Data Recorders (EDR). Many modern model vehicles are equipped with Event Data Recorders (EDR) in conjunction with the advanced occupant safety systems, similar to the "black box". EDRs are capable of electronically recording different crash parameters such as the ΔV and the vehicle's speed, brake status, lateral and longitudinal acceleration, seat-belt status, air-bag deployment and throttle position before and throughout the crash.

EDR provides the time history of the ΔV , which is helpful for reconstructing an accident. EDR detects when certain parameters have reached their threshold value and deploys the airbag and other restraint systems. Analysis of real world vehicle collisions enhances the understanding in this field and identifies how to better the effectiveness of safety technology and vehicles (Gabauer, et al., 2004), (Stigson, et al., 2012).

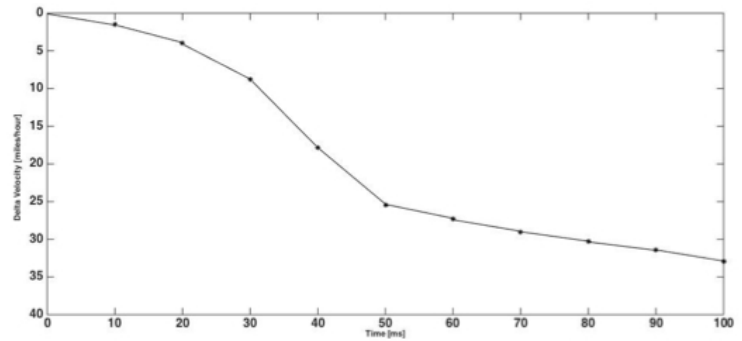


Figure 2.3 2007 model of Lexus after impact with Cadillac Eldorado 2002 model on the left picture and its EDR recorded ΔV on the right figure (<http://www-nass.nhtsa.dot.gov/nass/cds/SearchForm.aspx>, NASS case # 2012-043-194).

The ΔV and the acceleration during the crash influence how the vehicle occupants interact with installed passive safety equipment, such as airbags and their seat belt. Previous studies indicate a strong relationship between the accident metrics and the occupant's injury risk in real-world crashes. The assumption is that an increase in the ΔV correlates with higher injury severity. ΔV is measured by the EDR recorder and is considered a valid representation of the parameter. However the crash sequence can range longer than the EDR memory capacity, which can lead to incomplete pulse recordings during a crash event. Figure 2.4 indicates three types of ΔV recording from the EDR: the complete record, near complete record and incomplete record. The velocity curves with a fully recorded time history level out when the acceleration reaches zero (Iraeus & Lindquist, 2014).

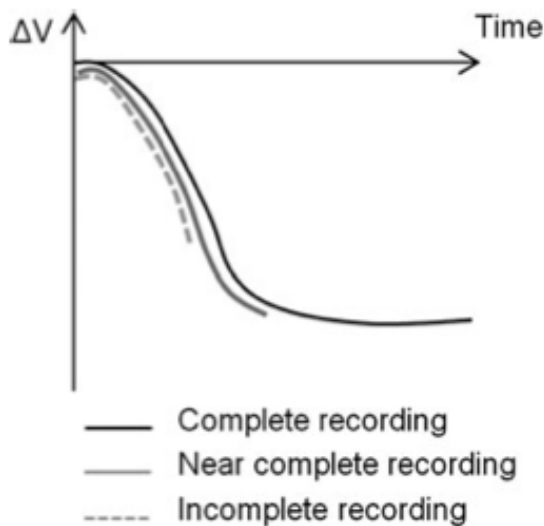


Figure 2.4 Three categories of EDR pulse recording (Iraeus & Lindquist, 2014).

The physical relationship between the ΔV and the acceleration are related through the crash event duration. The ΔV is the time integration of the acceleration pulse over the duration of the pulse. If the duration of the crash pulse is long, the ΔV during an impact can still reach high levels even though the ride down acceleration levels are low. However

because of a difficulty to retrieve real time history from real vehicle collision the research data on how the long crash pulse duration affects injury risk are limited (Ydenius, 2010).

2.7 Occupant Load Criterion

A previous study has analyzed the deceleration transferred to the occupant's seat, also known as a crash pulse. Crash severity characterization, which indicates the seriousness of the collision, can be analyzed and measured by different crash pulse criteria. This analysis is based upon the pulses where the occupants are at their maximum acceleration, the point in time when the vehicle velocity is zero, the velocity difference is at its highest or the average acceleration. The OLC model is based on the measurement of the restraining force applied to the occupant's chest (Lefer & Reboloso, 2012).

Figure 2.5 represents a single mass model of the occupant. The mass is linked to the vehicle by a spring with a stiffness depending on the relative distance between the mass (occupant) and the car interior. The restraint system is assumed to have two length parameters: L_0 which indicates the slack length (relative distance before the occupant is restraint), $L_0 = 65$ mm. and L_1 denotes the maximum restraint length (relative distance to decelerate the occupant to vehicle speed), $L_1 = 300$ mm. The OLC model assumes the initial slack to be 65 mm without occupant deceleration and the distance between the vehicle and the occupant to be 235 mm engaged to the restraint system, therefore, it can be assumed that the OLC is the occupant's response to the constant acceleration. Because of the seatbelt slack distance the force on the occupant in the first phase of the collision is very low (Lefer & Reboloso, 2012). The occupant experiences a free flight phase until the relative distance of 65 mm to the car is reached. The OLC indicates the minimum acceleration on the occupant, induced by a given crash pulse under the protection of the ideal restraint system (Park & Kan, 2010). When the occupant reaches the distance of 65 mm, it is assumed that the occupant is optimally restrained. Figure 2.5 indicates how the occupant is linked to the car by a spring with stiffness, depending on the relative distance between the occupant and the car interior (Lefer & Reboloso, 2012).

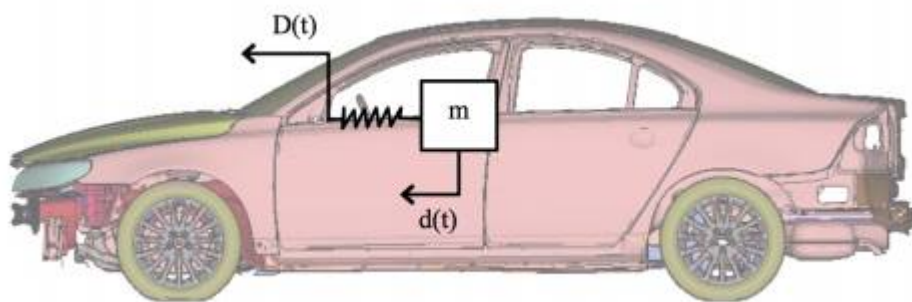


Figure 2.5 Single mass model used for calculation of the OLC (Lefer & Reboloso, 2012).

The OLC gives the possibility for rating a generated crash pulse severity with respect to generalized occupant decelerations, to indicate the minimum occupant acceleration

induced by a given crash pulse under the protection of the ideal restraint system (Park & Kan, 2010; Stein et al., 2011). In general, the OLC measures the restraint forces subjected to the driver from the crash event, based on deceleration only. The occupant is unrestrained until the relative displacement between the vehicle and the occupant reaches the time t_0 in Figure 2.6. The OLC pulse is then acting upon the occupant and starts to decelerate the occupant with a constant acceleration to vehicle speed until the relative displacement is t_1 in Figure 2.6.

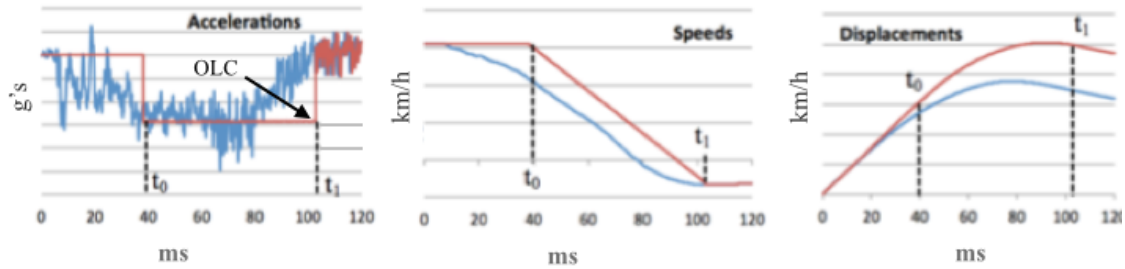


Figure 2.6 Calculations of OLC with acceleration, velocity and the displacement of the vehicle (blue curve) and the calculated equivalent for the occupant (red curve). OLC was used to assess passenger car acceleration (Lefer & Reboloso, 2012).

Figure 2.7 represents the occupant movement and the restrained force. When the curve reaches 65 mm (which is the relative distance before the occupant is restrained) it is assumed that the occupant is ideally restrained. Through multiple iterations, the OLC can then be calculated and identified from the area between the movements of the passenger from 65 mm to 300 mm (Ing & Teibinger, 2013). Because of the seatbelt slack, the force on the occupant in the first phase of the crash is low. The restrained force is therefore set at zero when the movements is between 0 and 65mm (c_1). The restrain force is applied to the occupant when the relative distance between the vehicle, and the occupant reaches 300 mm (c_2), which indicates t_1 in the graph in Figure 2.6 (Lefer & Reboloso, 2012).

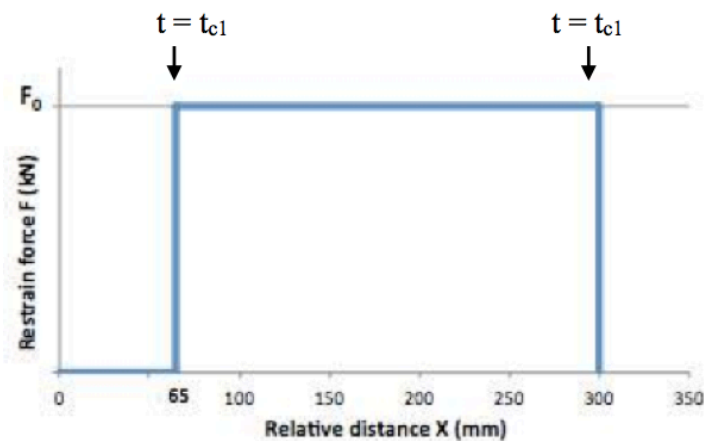


Figure 2.7 The restraint spring force (Lefer & Reboloso, 2012).

$$OLC = \frac{V_{c2} - V_{c1}}{t_{c2} - t_{c1}} \quad (2.3)$$

$$OLC(g) = \frac{OLC}{9.81m/s^2} \quad (2.4)$$

To determine the OLC value, the restraint force needs to be adjusted so that the occupant's maximum movement doesn't exceed 300 mm (crit2). The calculated restraint force is then the resulting constant deceleration value which gives the OLC value and calculated according to equation 2.3 and expressed in g's (Lefer & Reboloso, 2012).

2.8 Statistical Analysis and Computational Statistics

Statistical analysis is a technique, which gives the researcher the capability to analyze their data and investigate the association between outcomes and single predictions. In general, statistics is the practice of transforming raw data into knowledge. Maintaining the relevance of the statistics concerned is important; data should be collected to answer the questions in the research accurately. Statistics estimate how much data should be gathered, what conclusions the researcher can consequently draw from the data and if the data is reliable. Statistics will help the researcher to defend against the uncertainty and to estimate their results from their data. By using computational statistics, researchers are capable of storing and processing massive amounts of data (Dobson, 2002).

Simple linear regression is one quantitative variable predicting another while multiple regression is a simple linear regression with more independent variables. This study uses binary logistic regression analysis for the statistical analysis where the binary data does not have a normal distribution, which is a condition needed for most other types of regression. The binary logistic regression will be briefly described in the next section. The statistical program R, version 3.0.3, (R Core Team, 2014) was used to calculate the logistic regression and to make the injury risk curve. For the logistic regression, the R package "survey" was used (Lumley 2015).

2.8.1 Binary Logistic regression

Many educational research problems need a statistical analysis of the dichotomous of data. Logistic Regression methodology is used by many of these researchers in handling such type of dichotomous dataset. Binary logistic regression is a method used to explore the relationship and influence between the dependent binary data and the categorical independent variables (Agresti, 2002). It is a statistical method, commonly used in injury biomechanics to estimate injury risk and to indicate how the measurement variables affect the nominal variable. The regression analysis describes and assesses the relationship between the given dependent variable and all the variables that are independent. According to Weaver (Weaver et al., 2015), similar topics indicate significant results through the implementation of regression analysis. The goal of the logistic regression is to find an equation that best predicts the probability of a value of the y variable as a function of the x variables (Weaver et al., 2015).

Injury risk curves assessing the cumulative probability of moderate and serious injuries as a function of MAIS, longitudinal ΔV and OLC were developed using data from NASS. Logistic regression models were used to estimate the risk probability related to injuries and the injury severity for the head and the chest. Multiple logistic regression analysis was applied to all the samples to derive an analytical expression for MAIS2+ and MAIS3+ probability risk. Risk curves for MAIS2+ and MAIS3+ with and without intrusion were made based on logistic regression using R. Multiple Logistic Regression was performed according to the regression model indicated in equation 2.5. The curve equation presented in equation 2.6 below has MAIS2+ or greater and are represented as 1 or 0 in the equation dependently on if the occupant received MAIS2+ or not. ΔV is the longitudinal ΔV . The logistic model is defined by the equation below where the regression coefficients are the coefficients β . β_1 presents the intercept, β_2 presents the ΔV , β_3 presents the intrusion and β_4 presents the OLC.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 \quad (2.5)$$

$$p(MAIS) = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4)} \quad (2.6)$$

Logistic regression was performed according to the equation above with MAIS2+ or greater. The ΔV is the longitudinal ΔV ; and β_1 , β_2 , β_3 and β_4 are model parameters (Weaver et al., 2015). Though other variables such as whether the driver was drunk or the age of the driver can affect the injury severity the sample was too small to take other variables into the account in this study.

2.8.2 Injury Risk Curve

Injury risk curves estimate how the occupant's injury risk is dependent on a continuous variable (in this case the velocity change, the OLC and the intrusion severity). The risk curves are used for the safety assessment of passenger cars and to evaluate the effectiveness of safety systems. They are the basis for improving and evaluating vehicles occupant safety. The injury risk curves contain information about the biomechanical tolerance limit and the injury risk is a cumulative distribution function (CDF), which belongs to the distribution of the biomechanical tolerance limit. Injury risk curves were developed from data retrieved from the NASS-CDS 2003-2014 and vehicle models from 2002. Risk curves for MAIS2+ and MAIS3+ with and without intrusion were made based on logistic regression (Praxl, 2011).

A confidence interval is an approach to assessing the accuracy of the sample mean as an estimate of the mean and calculate boundaries within which we believe the actual value of the average will fall. In this study, the confidence interval will be calculated for the injury risk curves and plotted as a shaded area around the probability curve. Conditional plots with the 95% confidence interval level were made and plotted to the curves using the R package "visreg" (Breheny & Burchett, 2015; Field, 2000). The logistic regression and the calculation of the 95% confidence intervals were performed in statistical program 'R'.

3 Data Analysis and Results

As a part of the research method, data analysis is one of the key phases to evaluate and analyze the research questions and the hypotheses, which allows us to conclude some results through the research problem. The data analysis will be broken down into the descriptive analysis, the injury risk curves and the MAIS logistic regression where relations between the injury severity, ΔV , OLC and intrusion will be found.

The extracted EDR cases were analyzed from accidents sampled in the years 2003-2014. The dataset evaluated in this study composed of total of 1448 cases with frontal impact between the angle -60° and $+60^\circ$ with EDR record and airbag deployment. Out of the 1448 cases, only 661 cases included all the information needed (the injury severity, the intrusion information and the ΔV), from the 661 cases, only 219 cases had fully recorded data, which was needed for the calculation of the OLC. ΔV and OLC can be used to describe injury risk in general. Longitudinal ΔV and OLC were utilized in the logistic regression models for producing risk curves determining the risk of injury and intrusion for MAIS2+ and MAIS3+ with and without intrusion. Out of the 268 collisions, 49 resulted in intrusion and 219 exhibited no intrusion.

3.1 Descriptive Statistics

The descriptive analysis will be broken down into frequency tables and charts, the resulting injury severity, incidence of the velocity change and utilized in Chapter 3.1.1 (Descriptive statistics for variables). Frequency descriptive statistics will be demonstrated containing the mean, the variance, and the standard deviation, calculated with SPSS (version 23).

3.1.1 Descriptive Statistics for Variables

The outcome of the real world accident data retrieved from the NASS database during the period from 2003-2014 is shown in statistics and figures below. Table 3.1 presents number of collisions, the mean ΔV , the standard deviation and the range for both g and km/h with and without intrusion for all cases with complete ΔV recording. For all the accidents, the mean ΔV was 25,38 km/h. Table 2.2 and Table 2.3 show the distribution of injuries with and without intrusions for no injuries, for minor, moderate and severe injuries. 75,51 % of the passenger received MAIS2- injuries in accidents with intrusion (35 occupants), and 26,53% received MAIS2+ injuries (13 occupants), which is categorized as severe injuries. The mean ΔV for accidents with intrusion was 38,63 km/h and the standard deviation 22,85 km/h within the range 14,12 km/h – 75,67 km/h. The mean acceleration for cases with intrusion was 10,31g, and the standard deviation was 7,72g within the range 1,25g – 38,36g. One occupant received fatal injuries in an accident with intrusion at $\Delta V = 50,72$ km/h. Accidents without intrusion result in 79,07% MAIS2- injuries (208 occupants) and 4,59% MAIS3 injuries (10 occupants). No passenger received fatal injuries in a collision without intrusion. The mean ΔV in accidents without intrusion was 22,47 km/h and the standard deviation 10,82 km/h within the range 2- 56,96 km/h. The OLC for cases with intrusion is 10,31 g and the standard deviation was 6,69g within the range 0,01g -

38,36g. Figure 3.1 and Figure 3.2 indicate the distribution for the ΔV graphically. Figure 3.3 shows the correlation between the OLC and the ΔV .

Table 3.1 Mean ΔV , the range and the standard deviation for ΔV (table above) and g (table below).

	Frequency	ΔV (km/h)	Standard deviation (g)	Range (g)
Occupants	268	25,4	15,1	2 - 78
Cases with intrusion	49	38,6	22,9	14 – 76
Cases without intrusion	218	22,5	10,8	2 - 57

	Frequency	Deceleration (g)	Standard deviation (g)	Range (g)
Occupants	268	9,7	7,3	0,3 - 40
Cases with intrusion	49	10,3	7,7	1 - 38
Cases without intrusion	218	9,3	6,9	0,01 -38

Table 3.2 MAIS frequency for accidents without intrusion.

MAIS	Frequency	Percent (%)
0	86	32,09
1	105	39,18
2	17	7,80
3	10	4,59
4	0	0
5	0	0
6	0	0
Sum:	218	100

Table 3.3 MAIS frequency for accidents with intrusion.

MAIS	Frequency	Percent (%)
0	7	14,28
1	20	40,82
2	8	20,41
3	8	16,33
4	4	8,16
5	0	0
6	1	2,04
Sum:	49	100

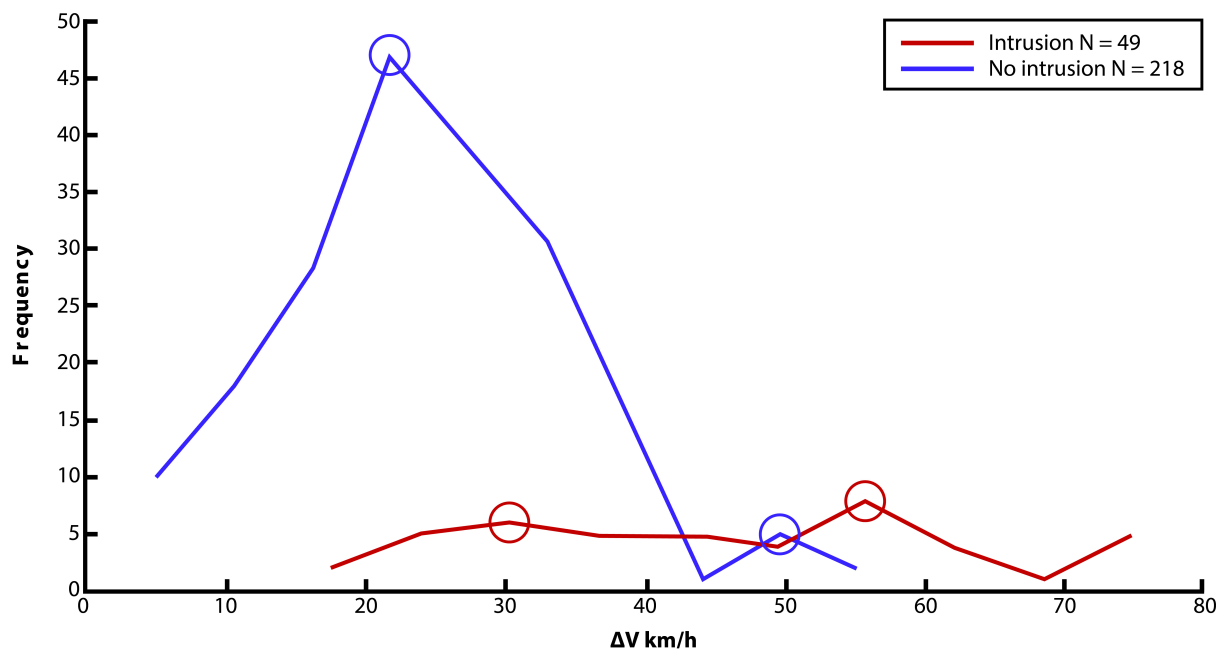


Figure 3.1 Longitudinal ΔV distribution with a circle around the peaks in the distribution. The red line represents intrusion and the blue line represents cases without intrusion.

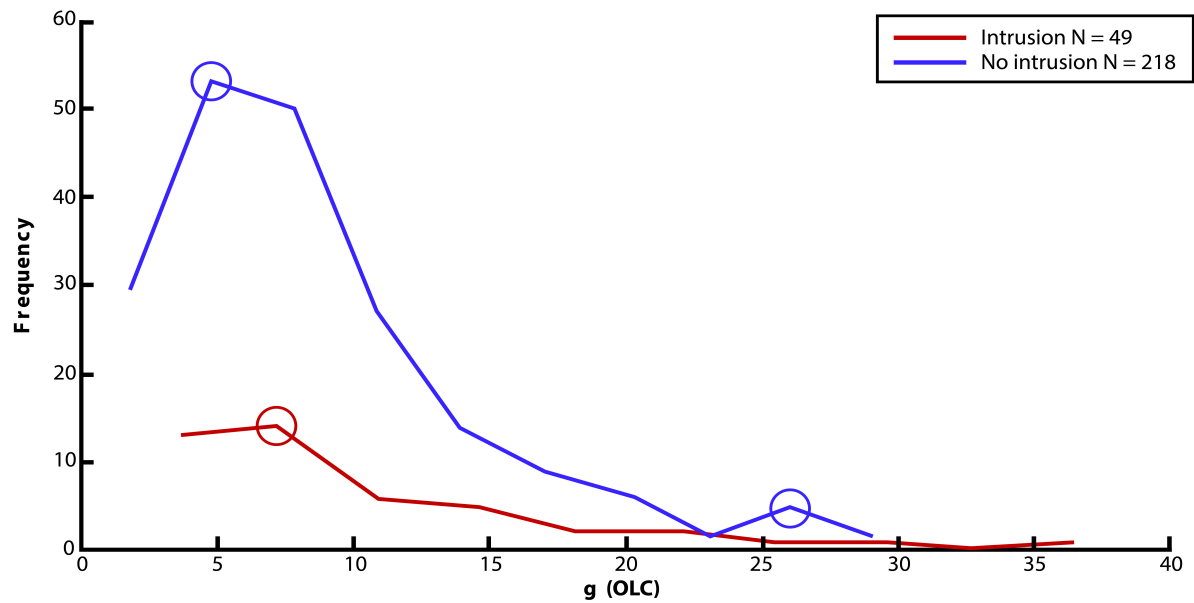


Figure 3.1 The OLC distribution with a circle around the peaks in the distribution. The red line represents intrusion and the blue line represents cases without intrusion.

As seen in Figure 3.1 and in Figure 3.2 accidents with intrusion occurred with greater ΔV . The accidents for no intrusion have a local maximum around 22km/h while accidents with intrusion have a peak around 55km/h.

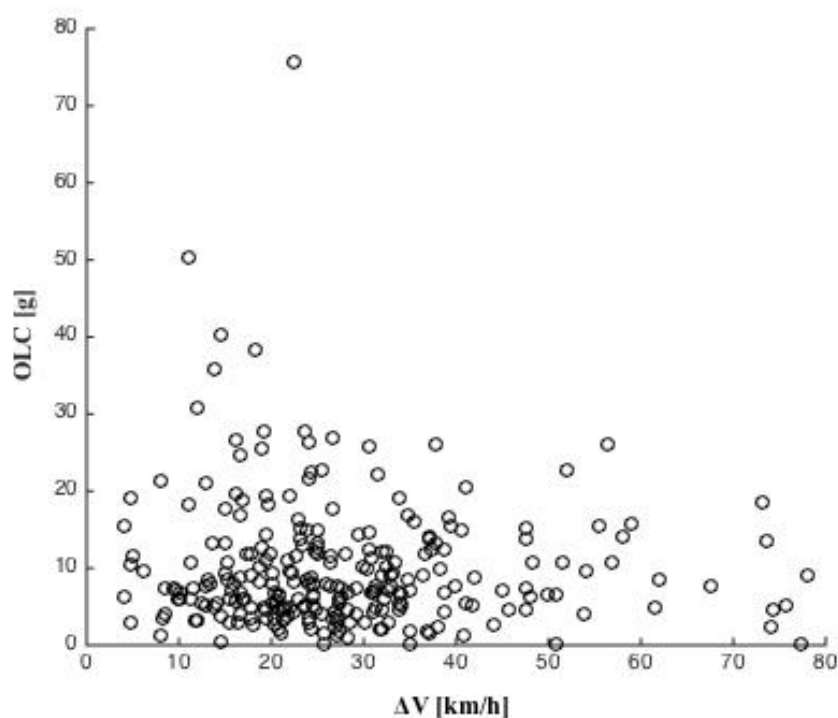


Figure 3.2 The correlation between estimated OLC and the ΔV

No linear relationship was found to be between the ΔV and the OLC indicated that they were not related.

3.1.2 Descriptive Statistics for Injury Biomechanics

During the analysis process, the injury source provided by the NASS investigators was analyzed. In total 268 cases with and without intrusion were analyzed and the occupants injury source retrieved from the NASS database (retrieved from <ftp.nhtsa.dot.gov/NASS>). The loading source of each MAIS from zero to six for the head, face, neck, chest, abdomen, and spine was established. The results of the frequency for each body part are presented in Table 3.4 for cases with intrusion and Table 3.5 for cases without intrusions. Out of a total of 268 occupants, 49 passengers were affected by intrusion resulting in injuries in the upper body according to Table 3.4. In total 219 occupants were analyzed for accidents with no intrusion resulting in injuries in the upper body according to Table 3.5.

For cases with intrusion, seven persons received head AIS2+ injuries. Injury with the score AIS 2, 3 and 4 head injury occurred from a contact with the airbag or the instrument panel. One individual received a fatal head injury. Eight individuals received chest MAIS2+ injuries, which can be related to the safety belt and from contacting the outboard side. One person received MAIS2+ abdomen injury and three received MAIS2+ spine injury. For cases without intrusion, a total of ten persons received head AIS2+ injury. Occupant with the score AIS2 and AIS3 head injury occurred from a contact with the airbag or the pillar. Six individuals received chest MAIS2+ injuries, which occurred from the safety belt. One individual received AIS2 abdomen injuries and one received AIS2 spine injury.

Table 3.4 MAIS Injuries for each body region from accidents with intrusion.

Body region	MAIS						
	0	1	2	3	4	5	6
Head	38	4	3	2	1	0	1
Face	31	16	2	0	0	0	0
Neck	42	7	0	0	0	0	0
Chest	29	12	2	2	4	0	0
Abdomen	34	14	1	0	0	0	0
Spine	43	3	2	1	0	0	0

Table 3.5 MAIS Injuries from accidents without intrusion

	MAIS						
Body region	0	1	2	3	4	5	6
Head	204	4	9	1	0	0	0
Face	199	19	0	0	0	0	0
Neck	210	8	0	0	0	0	0
Chest	169	43	3	3	0	0	0
Abdomen	208	9	1	0	0	0	0
Spine	187	31	1	0	0	0	0

3.2 Logistic Regression Models with Intrusion as a Binary Number

This part of the report will go through the calculation of the strength of the relationship between injury severity versus the velocity change and the OLC. Based on the distribution of injuries in Table 3.2 and Table 3.3 the relationship between the probabilities of injury risk, ΔV , OLC and intrusion were calculated with multiple logistic regression analysis for accidents with and without intrusion for all cases. The risk curves for MAIS2+ and MAIS3+ and AIS2+ chest injury is presented in Figure 3.4 through Figure 3.6. The data used to create the risk curves were chosen to be cases with entirely recorded time history for ΔV . Acceptable data, used to plot the risk curves, are accidents with ΔV where the calculated occupant movement reached 300 mm with and without intrusion. Risk curves for MAIS2+ and MAIS3+ injury risk versus longitudinal ΔV with intrusion were produced for 21 individuals who received MAIS2+ and 13 individuals who received MAIS3+. Injury risk curves for accidents with no intrusion were produced for 27 individuals with MAIS2+ and ten individuals who received MAIS3+.

The corresponding shaded area in the chart represents the 95 percent bound for the confidence interval calculated for the longitudinal ΔV . The velocity change for cases with intrusion ranges from 14,12 km/h to 75,67 km/h and cases without intrusion varies from 2,0 km/h to 56,96 km/h. The vertical axis represents the probability, and the horizontal axes represent the velocity change in km/h where the OLC is either 5g or 20g. For accidents with intrusion, 49 cases could be sampled and in total 219 cases for accidents without intrusion. The result of logistic regressions estimates the relationship between the occupant's injury, the intrusion and the ΔV or between the occupant's injury, the intrusion and the OLC. The intercepts are presented in Table 3.6 through Table 3.8.

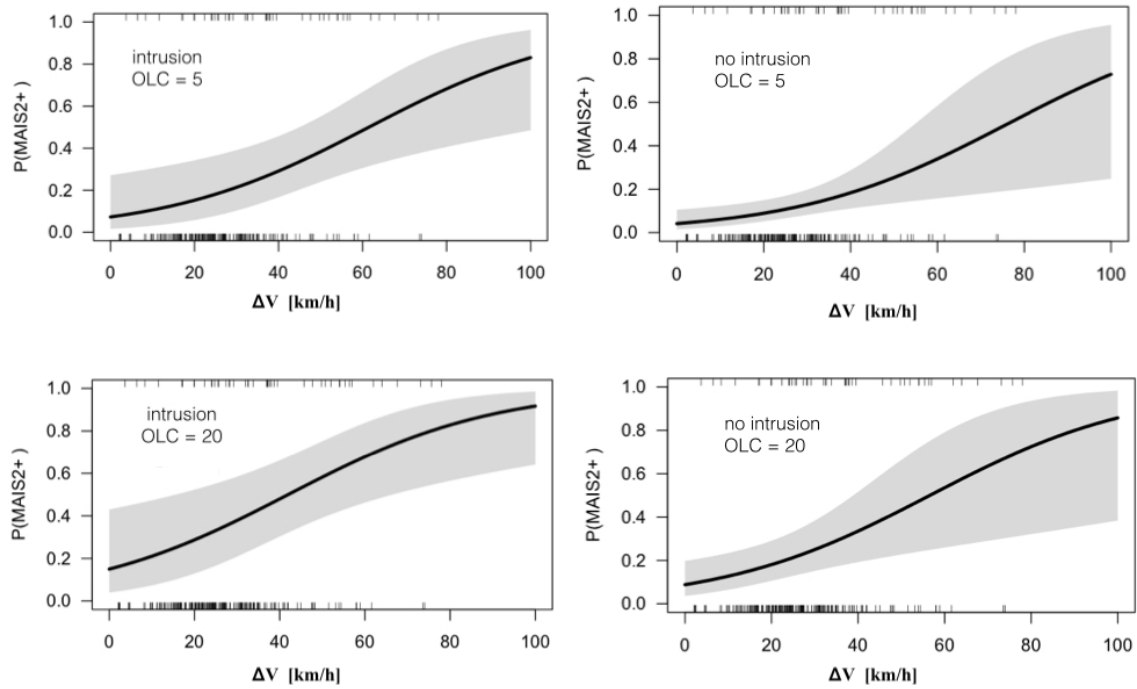


Figure 3.4 MAIS2+ Injury risk curves with 95% confidence intervals for accident containing OLC 5 and OLC 20. The injury risk curve is plotted versus the longitudinal ΔV : Intrusion (left) and no intrusion (right).

Table 3.6 Regression model for prediction of the risk of MAIS2+ for accident with and without intrusion. This table includes the intercept of the dependent variables above and dependent variable below.

Coefficients	Estimate of model parameter	Std. error	Pr(< z)	t-value	Significance
Intercept	-3.415	0.584	1.63e-08	-5.848	***
ΔV	0.041	0.015	0.006	2.790	**
Intrusion	0.603	0.462	0.193	1.304	
OLC	0.054	0.025	0.035	2.116	*

* indicates statistical significance: 0.001*** 0.01** 0.05* 0.001

The results from the binary logistic regression in Table 3.6 shows that there is a significant intercept, a significant ΔV parameter, a significance for the OLC parameter but no significance in the intrusion parameter since the p value is 0.19 and is above 0.05. Figure 3.4 presents the relationship between MAIS2+ injury and the ΔV , OLC at 5g and OLC at 20g for accidents with and without intrusion for fully recorded data. The upper-risk curve to the left in Figure 3.4 determines the probability for MAIS2+ with intrusion at OLC = 5g. The figure has a line in the center of the response range showing a linear relationship. As the ΔV increases, the slope also increases indicating that the risk to receive MAIS2+ injury

also increases. The risk curve indicates that the risk of receiving MAIS2+ at a velocity change of 20 km/h is approximately 18% and at 60 km/h the risk is approximately 57%. Because of limited data for injuries with intrusion, the confidence interval is wide with a little more narrow CI level at 40km/h and 60km/h indicating that the most of the data occurs within that range. At OLC = 20g for accidents with intrusion the probability for receiving MAIS2+ injury increases. The injury risk curves for OLC = 20g with intrusion shifts up compared to the risk curve at OLC = 5g. The risk of receiving MAIS2+ injury with intrusion at OLC = 20g has a slope covering the response range and indicating that the risk of receiving MAIS2+ injury at 20 km/h is approximately 30% and at 60 km/h the risk is approximately 70%. The CI level is wide. The risk of receiving MAIS2+ injury without intrusion at OLC = 5g has narrow CI level in the beginning, and the risk of receiving MAIS2+ injury at 20 km/h is approximately 10% and approximately 30% at 60 km/h. The risk of receiving MAIS2+ injury without intrusion at OLC = 20g has a slope covering the response range and indicates that the risk of receiving MAIS2+ injuries at 20 km/h is approximately 10 % and at 60 km/h the risk is 60%. The confidence interval is narrow in the beginning and wide after 40km/h. The result from the logistic regression indicates a significant intercept, a significant ΔV parameter, significance for the OLC parameter, but no significance at 0,05 level for the intrusion parameter where the p-value is 0.19.

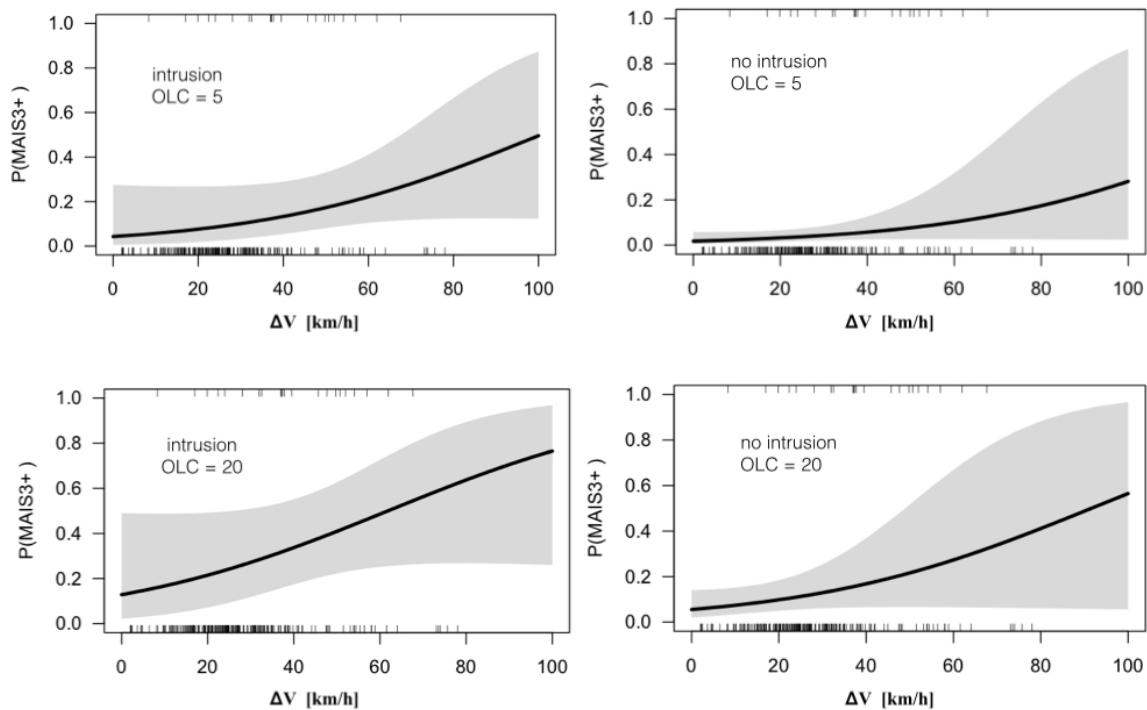


Figure 3.5 MAIS3+ Injury risk curves with 95% confidence intervals for accident with OLC 5 and OLC 20: The injury risk curve is plotted versus the longitudinal ΔV : intrusion (left) and no intrusion (right).

Table 3.7 Regression model for prediction of the risk of MAIS3+ in accidents with intrusion and fully recorded time history for the velocity change. This table includes the intercept of the dependent variables.

Coefficients	Estimate of model parameter	Std. error	Pr(< z)	t-value	Significance
Intercept	-4.432	0.734	6.03e-09	-6.035	***
ΔV	0.031	0.019	0.10404	1.632	
Intrusion	0.921	0.687	0.18166	0.182	
OLC	0.0799	0.030	0.00869	0.009	**

* indicates statistical significance: 0.001*** 0.01** 0.05* 0.001

The results from the binary logistic regression in Table 3.7 indicates that there is a significant intercept and significance for the OLC parameter but no significance in the intrusion parameter since the p value is 0.18 and in the ΔV where the p value is 0.10 and is above 0,05. The number of observations for MAIS3+ is too low to run a regression. The more observation the more the parameters of the model will be constrained by the data, and the more confident the model will become.

Figure 3.5 indicates the relationship between MAIS3+ and ΔV , intrusion and the OLC. The figure which indicates the risk of receiving MAIS3+ injury with and without intrusion at OLC = 5 g and 20g. The risk of MAIS3+ injury, which is classified as a serious injury according to the abbreviated injury scale, is approximately 10% for the velocity change at 60 km/h for OLC = 5g with intrusion. The wide CI level can be related to that only 13 individuals received MAIS3+injuries. When impact with OLC = 20g and intrusion occurs the risk of receiving MAIS3+ injury increases, at 20km/h the risk is estimated to be 25% and at 60km/h it is 50%. The risk of MAIS3+ injury at OLC = 20g with no intrusion has a line that increases rapidly after reaching the velocity change a 60km/h. The probability of MAIS3+ injury with no intrusion is approximately 30% at 60 km/h. A narrow confidence interval, in the beginning, indicates that all the injuries occurred in that range which corresponds to the data. The results from the Linear Regression gives empirical support that OLC and ΔV influences the injury risk but no empirical support for intrusion.

3.3 MAIS Logistic Regression Models for Head and Chest

AIS2+ injury probability relationship for head and chest for belted occupants in a single frontal impact were calculated with binary logistic regression. Figure 3.6 presents the injury probability for chest injury and indicates the probability relationship for AIS2+ chest injury. The intercepts results from the logistic regression are presented in Table 3.8. In total 49 accidents with intrusion and 218 with no intrusion were analyzed for estimating

head and chest injury. For cases with intrusion seven occupants received AIS2+ head injury and four received AIS3+ head injury. Eight occupants received AIS2+ chest injury and six individuals received AIS3+ chest injury. For accidents with no intrusion, nine passengers received AIS2+ head injury, one received AIS3+ head injury, three individuals received AIS2+ chest injury and three received AIS3+ chest injury.

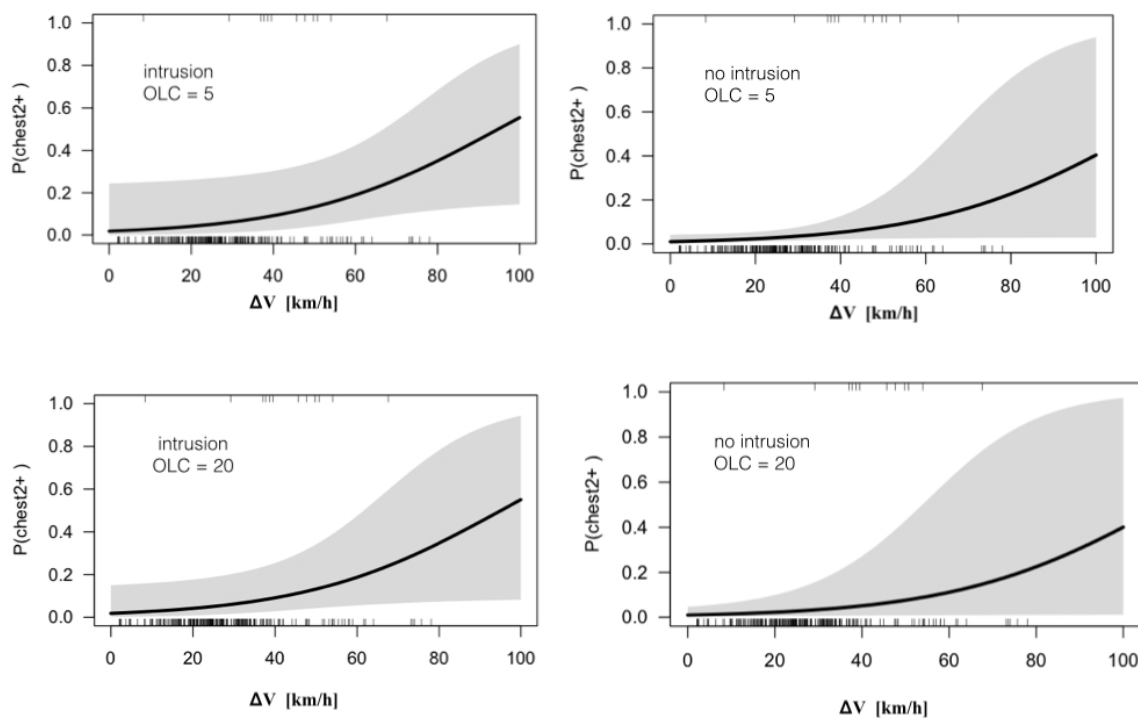


Figure 3.6 Injury risk curves with 95% confidence intervals estimated for the chest. The injury risk curve is plotted versus the longitudinal ΔV : Intrusion (left) and no intrusion (right).

Table 3.8 Regression model for prediction of the risk of AIS2+ for chest injuries in accidents with intrusion and fully recorded time history for the velocity change. This table includes the intercept of the dependent variable and the independent.

Coefficients	Estimate of model parameter	Std. error	Pr(< z)	t-value	Significance
Intercept	-4.552	0.897	8.01e-07	-5.070	***
ΔV	0.042	0.021	0.053	1.945	*
Intrusion	0.606	0.955	0.526	0.634	
OLC	-0.001	0.057	0.986	-0.018	

* indicates statistical significance: 0.001*** 0.01** 0.05* 0.001

The injury risk curve with intrusion for the chest indicates a 20% probability of receiving AIS2+ injury when both OLC curves at 5 and 20 is approximately at 60km/h. The risk of receiving AIS2+ chest injury without intrusion did not show any relationship within the first 40km/h. After receiving 40km/h the slope increases with high confidence interval level. The AIS2+ chest injury occurred between the range of 29,18km/h and 47,66km/h, which affects the wide confidence interval level and the high increase in the slope. The ΔV , the intrusion and the OLC in Table 3.8 does not show any significance, only the intercept is significant.

It was found that AIS3+ chest injury in cases with intrusion occurs between ΔV at 50 km/h and 80 km/h while the injury without intrusion for AIS3+ chest injuries occurs between ΔV 37km/h and 47km/h for the three cases. The risk of receiving AIS3+ chest injury did not show any relationship and was not significant. Due to small sample, there was no possible way to draw any conclusion for the risk of head injuries or AIS3+ chest injuries.

3.4 Logistic Regression Models with Intrusion as a Categorical Variable

This part of the study will go through intrusion severity and the relationship between the severity and risk of receiving MAIS2+ injury. The intrusion was defined as the maximum of longitudinal intrusion. Risk curves were made with the binary logistic regression based on the distribution of injuries in Table 2.2 and Table 2.3 and related to a classified intrusion level from 0-5. The intrusion level is categorized into 5 categories according to the Nass/CDS. In total 49 cases with intrusion were analyzed and the severity of the intrusion was categorized into 6 groups presented in Table 3.9. Figure 3.7 shows a histogram for the number of cases with intrusion where ΔV was fully recorded during the impact. The intrusion occurred in the instrument panel, in the windshield and in the steering assembly. Injury risk curves were made with logistic regression for the relationship between the velocity change and the intrusion severity. Figure 3.8 describes the probability relationship between the MAIS2+ injury, the intrusion severity and the ΔV for each of the six intrusion categories at OLC 5g and OLC 20g. The probability is shown in Table 3.10.

Table 3.9 The six categories for the intrusion severity.

Category	Intrusion (cm)
0	3-7
1	8-14
2	15-29
3	30-45
4	45-59
5	60+

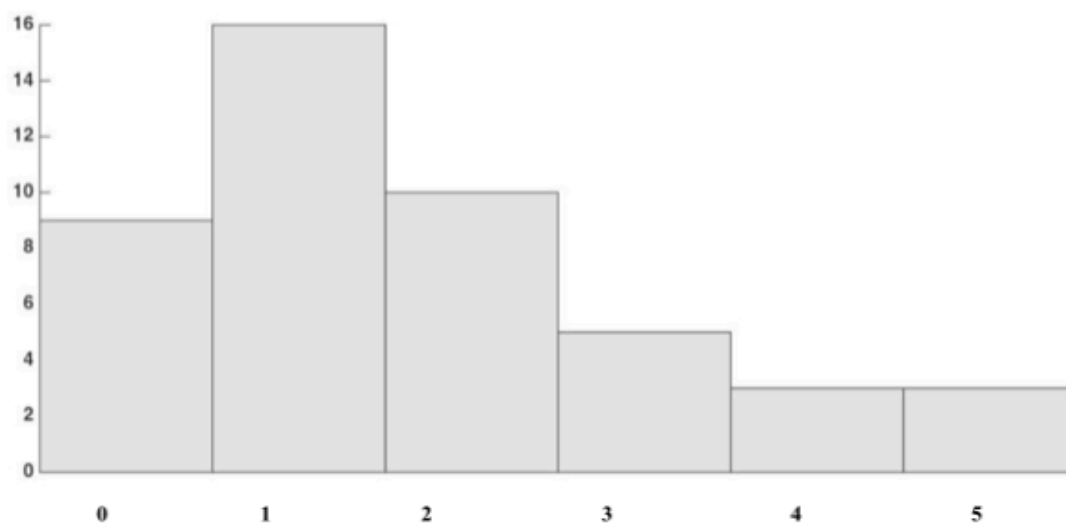


Figure 3.7 Frequency of accidents with intrusion severity for fully recorded time history. The frequency is presented on the y-axis and the intrusion level on the x-axis.

Table 3.10 Risk of MAIS2+ injuries at a certain level of intrusion when ΔV is 40 km/h and OLC is 5g and 20g.

Intrusion (cm)	ΔV (km/h)	OLC (g)	Probability (%)
0 (3-7)	40	5	19
	40	20	31
1 (8-14)	40	5	20
	40	20	38
2 (15-29)	40	5	23
	40	20	42
3 (30-44)	40	5	25
	40	20	50
4(45-59)	40	5	30
	40	20	52
5(60+)	40	5	38
	40	20	58

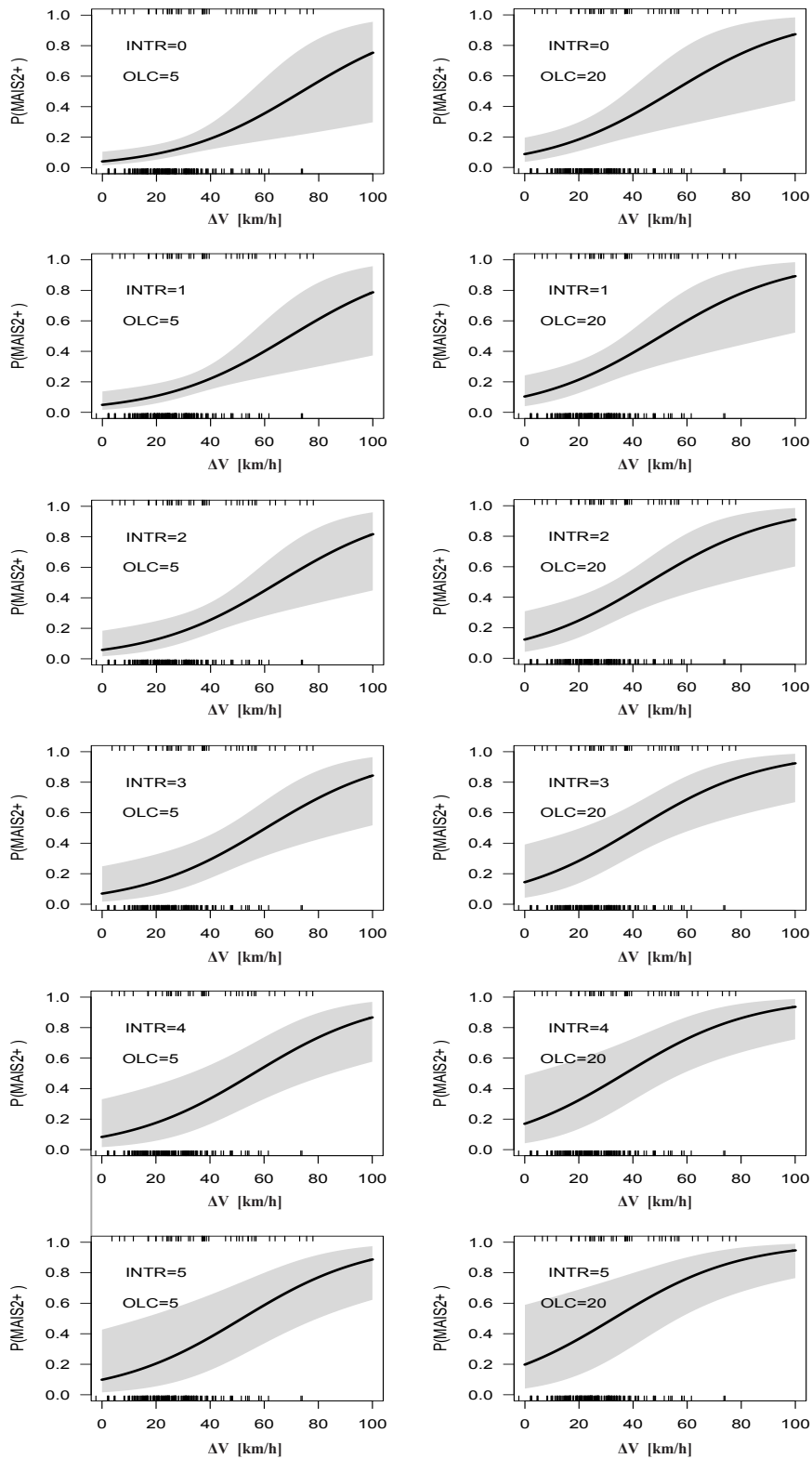


Figure 3.8 Injury risk curves with 95% confidence intervals estimated for the intrusion severity from 0-5. The injury severity is presented on the y-axis. The injury risk curve is plotted versus the longitudinal ΔV .

Table 3.11 Regression model for prediction of the risk of intrusion severity versus ΔV for fully recorded time history. This table includes the intercept of the dependent variables.

Coefficients	Estimate of model parameter	Std. error	Pr(< z)	t-value	Significance
Intercept	-3.428	0.589	1.92e-08	-5,283	***
ΔV	0.043	0.014	0.003	2.998	**
Intrusion (Categorized)	0.189	0.135	0.162	1.402	
OLC	0.054	0.026	0.04	2.068	*

* indicates statistical significance: 0*** 0.01** 0.05*

Figure 3.8 shows the MAIS2+ injury risk curves when the intrusion is classified into six groups and ranges between 3-60 cm versus the ΔV . Table 3.10 indicates the MAIS2+ injury risk at a certain intrusion level, when the ΔV is 40km/h and the OLC is 5g and 20g. The results from the binary logistic regression presented in Table 3.11 shows a significant intercept, a significant ΔV parameter, a significant OLC parameter, but not significance for the intrusion parameter where the p-value is equal to 0.16.

4 Discussion

This study provides an indication of the relationship between injury, ΔV , and intrusion. In this study, the existing metrics for evaluating the intrusion and the pulse severity are reviewed and categorized. The intrusion was classified into six groups and the pulse into two: five and twenty g's. A total of 268 accidents where 49 results in intrusion into the occupant compartment were analyzed. This chapter elaborates on the above results from the analysis and compares the results to the project's research questions, which was: How do velocity changes, pulse, and intrusion affect the occupant's injury risk severity? How does the presence of the intrusion affect the occupant's injury for a given crash severity? Logistic regression was used to estimate injury risk curves for single frontal impact. The objective of this study was to assess the injury probability of MAIS2+ and MAIS3+ severity and the ΔV , the OLC and the intrusion severity.

The study only focused on vehicles involved in frontal impacts between the angle 10 and 2 o'clock (60 and -60) and did not consider other crash modes, e.g., side, and back impact. The study also only assessed the injury in the upper body and did not consider the effect from intrusion in the floor or toe pan. The data used in this study were based on data from real-life frontal crashes and retrieved from the NASS database, which is publicly available in SAS files. However, one of the ΔV limitations is that the time over which the pulse of the accident occurs, the time history (Δt), is not publicly available, except in a pdf format. The data from the pdf files could therefore not be gathered like the other data from the SAS files (German, Comeau, McClafferty, Shkrum, & Tiessen, 2007). Because the time history from the EDR database was not publicly available, the OLC calculation was done at the Virginia Tech University with a Matlab code created for this project. Another limitation of this study is the logistic regression analysis. Due to the small sample size (or only 268 crashes), there were only 49 that resulted in intrusion into the occupant's compartment. Therefore it was hard to find any significant categorical predictor variables.

Although the data set was limited to single event crashes, EDRs sometimes don't interpret as a single event. A crash sequence, such as a single head-on collision could have been seen as two or more separate events according to the EDR, which will explain some small ΔV in some cases. This could occur for a multitude of reasons, but the most common are that the EDRs tend to log an event for when they 'wake up'. This 'wake up' happens when the EDR recognizes that an accident is actually occurring (generally primarily triggered by a particular acceleration threshold that must be exceeded). Going back to our head-on example, some EDRs may realize that as two events, the 'wake up' and then the rest of the accident sequence until the vehicle comes to rest, while we see it as one. So why is this a problem for the MATLAB script? When EDR logs more than one event, it records two separate time series, one for each event, both of which will restart logging at time 0. Therefore, if an accident sequence is 300 ms long, it may have one time series for 'wake-up' from 0-50 ms and then another for the rest of the crash sequence from 0-250 ms (since the events occur consecutively but EDR event time series always start at time 0). The MATLAB script was not programmed to see more than one-time series for a single crash. Therefore, for crashes with more than one EDR event, the script would not accurately calculate the OLC, probably for a multitude of reasons. What needs to be done in the future

is that the script needs to be modified so that it can identify when a single crash/EDR logs more than one event. When there is indeed more than one event and corresponding time series, the script should identify which sequence yields the most severe (largest) and use that sequence to calculate the OLC.

There are not many kinds of literature to find regarding risk curves on passenger cars in frontal collisions from real life scenarios except from the EDR. Not all vehicles are equipped with EDR records and not all impacts results in airbag deployment, which limited the amount of data sampling for this study. An important factor is also that EDR recorder is reasonably precise but not perfect. EDRs have been shown underreport the ΔV measured by onboard reference accelerometers by 3-7% in full frontal crash tests (Gabler. et al 2008; Tsoi. et al 2013).

One source of error can be found in the lost acceleration signal in the beginning and/or the end of the EDR recording. Real crash is not as well defined and in the same sense as a lab crash when the start of the accident is the first point of impact, and the end is when the acceleration levels out and becomes stationary zero. The lost signal, in the beginning, can be explained because the first point of impact on the vehicle is typically plastic parts which are virtually impossible to detect with today's sensors and the deformation of these plastic parts does not give significant acceleration response in the vehicle (Iraeus & Lindquist, 2014).

One limitation regarding the injury severity is that the AIS scale does not represent a linear scale, and the difference between several scores is not the same. The score between AIS-4 and AIS-5 is not the same as for AIS-1 and AIS-2.

According to Table 3.5 and Table 3.6 when an intrusion is a binary number, the ΔV is more significant for minor injuries, and the OLC is a stronger predictor for severe injuries. The p-value for the ΔV is 0.0057 for MAIS2+ but 0.10404 for MAIS3+. The p-value for the OLC is 0.0354 for MAIS2+ and 0.00869 for MAIS3+. When categorizing the intrusion, the results from the logistic regression shows a significant intercept, significance for the ΔV , significance for the OLC but no significance for the intrusion. There is slightly more significance for the categorical intrusion compared to the binary intrusion parameter but still no significance at the 0.05 level. These results indicate that we cannot say that the intrusion is statistically significant for the injury outcome.

As seen in Figure 3.1 and Figure 3.2, accidents with intrusion occur with higher ΔV . The accidents with no intrusion have a peak around 22 km/h while accidents with intrusion have a peak around 55km/h. This indicates that higher velocity effects the intrusion and the injury severity. One individual received fatal chest injury, which can be related to contacting the instrument panel. However, the intrusion was not high compared to the high ΔV or 50,72 km/h. Two individuals received fatal head injury by contacting outboard side (the pillar) in the accident where the ΔV was 77,39 km/hour. These results also indicate that the injury severity is related to the ΔV and the pulse.

Table 3.1 shows a big difference in ΔV (42% difference) for cases with and without intrusion and a small difference for OLC in cases with and without intrusion (9,5 % difference). There are greater ΔV and higher pulse for cases with intrusion than without. These results imply that the intrusion is related to the ΔV and the OLC. The ΔV and the OLC are therefore an important factor for the resulting injuries.

The results provide new information for vehicle designers showing how intrusion and ΔV are distributed in crashes. The analysis was restricted to modern vehicles and illustrates crash severity thresholds where intrusion begins to occur and influence injury risk. The analysis also helps understand the relevance of crash pulse and the acceleration levels experienced by occupants before the onset of intrusion. Intrusion related injuries below standard design crash severities (>56 km/h ΔV) also highlights issues where crash compatibility may be a relevant safety performance factor.

This study only assessed vehicles involved in frontal impacts between the angle 10 and 2 o'clock (60 and -60) and did not consider other crash modes, e.g. side and back impact. This study also only assessed the injury in the upper body and did not consider the effect from intrusion in the floor or toe pan. The age of the occupant was not taking into account because of a small sample. This factors affects the injury and should be taking into account in future studies.

Similar study with risk curves have been developed based on Crash Pulse Recorder data (CPR) and GIDAS data. However, there are not many literatures to find regarding risk curves on passenger cars in frontal collisions from real life scenarios except from the EDR. Not all vehicles are equipped with EDR records and not all impacts results in airbag deployment, which limited the amount of data sampling for this study. An important factor is also that EDR recorder is reasonable precise but not perfect. EDRs have been shown underreport the delta-v measured by onboard reference accelerometers by 3-7% in full frontal crash tests (Gabler. et al 2008; Tsoi. et al 2013). In upcoming years, an increasing number of vehicles will be equipped with side airbags, which require sensors for lateral motion. A large additional number of NASS/CDS cases containing EDR data with information regarding lateral ΔV in addition to the longitudinal ΔV will than be available. When the number of cases, particularly cases containing information regarding the occupant's injury is large enough, it will be easier to analyze the injury risk. The results indicate that today too few cases containing the velocity change, the injury information and the intrusion exist to get accurate results. The raw data containing the time history of the velocity change will be needed in future studies

5 Conclusions

The objective of this study was to assess the probability of the MAIS severity and the ΔV , OLC and the intrusion severity and what predict serious injury in real scenarios. It was found that the OLC interpreted as a crash pulse severity metric did not give direct information on occupant injury risk levels. Therefore, the OLC shows only the conditions supplied by the vehicle structure for the restraint system to operate in. Binary and multiple logistic methods were used to analyze and present the results. This study provides an indication of the relationship between the occupant's injury, the ΔV , the OLC and the intrusion in real world accidents. To be able to understand these key factors, the study has:

- Calculated the Occupant Load Criterion (OLC), which estimates the occupant's mean acceleration.
- Made probability relationship with binary logistic regression for MAIS2+ and MAIS3+ for belted occupants in accidents, with and without intrusion, versus the ΔV , the OLC and the intrusion to estimate the risk of a specific injury severity for a particular velocity of the collision. The risk curve was made with the intrusion as categorical and as a binary number.
- Compared the OLC and the ΔV to estimate which parameter gives a significantly better result.

Of the 268 cases identified, only 50 cases involved vehicle intrusion data. Crash severity, as described by measured ΔV , was biased towards lower severity (under 35 km/h) with a maximum reported ΔV of 78 km/h. Intrusion to the passenger compartment requires enough front end damage to initiate deformation of the interior surfaces. As expected, cases with intrusion had higher ΔV on average, than those without intrusion. The accident data shows that the injury severity is greater for accidents with intrusion and the risk of injury severity increases with higher velocity and greater intrusion. When combining the ΔV and the OLC a greater OLC results in a higher probability of injury. However, according to this study, the correlation between the OLC and the ΔV can be showing an interesting situation where the crash severity with OLC is not at all related to ΔV and can be a function of vehicle design. OLC is a stronger predictor of severe injury where ΔV is stronger for minor injuries. The classified intrusion gives a slightly more significance compared to the binary intrusion parameter, but there were still no significant at the 0.05 level. The intrusion starts earlier for MAIS2+ and the risk of receive MAIS2+ and MAIS3+ injury raises with a higher ΔV , with a higher pulse and a higher intrusion.

The study provides new insights to vehicle design and real world crash performance. Designers of passenger cars must be aware of self and partner protection issues and this study provides insights to frontal crash protection. The information is also relevant to future safety strategies where the shift in crash severity due to active safety systems will influence the crash severity distribution, but not the injury risk curve. Thus this study has long term applications for frontal crash protection.

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Appendix A

A.1.1 Example R Code

```
# Read data (header=true means that the first row is treated as a header), sep=separator character
Data<-read.table('deltav_olc_intr.csv',header=TRUE,sep=';') ## reading the data into R
#
# n=248
#
# Variables:
#-----
# "olc"
# "timeAtcrit1"
# "TimeAtcrit2"
# "Dv"
# "MAISADJ"
# "intr_cat"
# "CASENO"
# "PSU"
# "caseyear"
# "MAIS2p"
# "MAIS3p"
# "HEAD2p"
# "HEAD3p"
# "CHEST2p"
tmp<-(-Data$Dv)
Data$Dv<-tmp
tmp<-(-Data$olc)
Data$olc<-tmp
#
# Define logit function
logit<-function(z) {ll<-log(z/(1-z))}
library(plotrix)
y<-Data$MAIS2p
xt<-Data$Dv
# The length of the column is the number of cases, = dim(Data)[2]
xt_sc<-rep(1.0,dim(Data)[1])
hh<-weighted.hist(xt,xt_sc,plot=F)
#hh<-hist(xt,plot=F)
x2<-xt
for (kk in (1:length(hh$breaks)-1)) {
  x2[xt<=hh$breaks[kk+1] & xt>hh$breaks[kk]]<-hh$mid[kk] }
tt<-table(y,x2)
levels<-as.numeric(names(as.data.frame(tt[,])))
tmp<-matrix(0.0,dim(tt)[1],dim(tt)[2])
#for(j in (1:2)) {
for(j in (1:dim(tt)[2])) {
```



```

for(k in (1:length(xt_sc))) {
  if ((abs((x2[k]-levels[j]))<0.00001)){
    if (y[k]){
      tmp[2,j]<-tmp[2,j]+xt_sc[k]
    } else {
      tmp[1,j]<-tmp[1,j]+xt_sc[k]
    }
  }
}
}
}
ttt<-logit(tmp[2,]/apply(tmp,2,sum))
#
plot(sort(unique(x2)),ttt,xlab="grouped x",ylab="log-odds")
library(survey)
dstrat<-svydesign(id=~1,weights=xt_sc, data=Data)
gg.surv<-svyglm(MAIS2p~Dv,
design=dstrat, family=quasibinomial())
summary(gg.surv)
xt<-seq(0,100,1)
yt<-matrix(0.0,101,2)
{
tmp<-predict(gg.surv, newdata=data.frame(Dv=i-1.0),se.fit=TRUE)
yt[i,1]<-as.data.frame(tmp)$link
yt[i,2]<-as.data.frame(tmp)$SE
}
lines(xt,(yt[,1]),type="l")
lines(xt, (yt[,1]+1.96*yt[,2]), lty=2)
lines(xt, (yt[,1]-1.96*yt[,2]), lty=2)
library(plotrix)
y<-Data$MAIS2p
xt<-Data$intr_cat
xt_sc<-rep(1.0,dim(Data)[1])
hh<-weighted.hist(xt,xt_sc,plot=F)
#hh<-hist(xt,plot=F)
x2<-xt
for (kk in (1:length(hh$breaks)-1)) {
  x2[xt<=hh$breaks[kk+1] & xt>hh$breaks[kk]]<-hh$mid[kk] }
tt<-table(y,x2)
tmp<-matrix(0.0,dim(tt)[1],dim(tt)[2])
#for(j in (1:2)) {
for(j in (1:dim(tt)[2])) {
  for(k in (1:length(xt_sc))) {
    if ((abs((x2[k]-levels[j]))<0.00001)){
      if (y[k]){
        tmp[2,j]<-tmp[2,j]+xt_sc[k]
      } else {
        tmp[1,j]<-tmp[1,j]+xt_sc[k]
      }
    }
  }
}
}
}
ttt<-logit(tmp[2,]/apply(tmp,2,sum))
#
plot(sort(unique(x2)),ttt,xlab="grouped x",ylab="log-odds")

```

```

library(survey)
dstrat<-svydesign(id=~1,weights=xt_sc, data=Data)
gg.surv<-svyglm(MAIS2p~intr_cat,
design=dstrat, family=quasibinomial())
summary(gg.surv)
xt<-seq(0,100,1)
yt<-matrix(0.0,101,2)
for (i in (1:101)) {
  tmp<-predict(gg.surv,
newdata=data.frame(intr_cat=i-1.0),se.fit=TRUE)
  yt[i,1]<-as.data.frame(tmp)$link
  yt[i,2]<-as.data.frame(tmp)$SE
}
lines(xt,(yt[,1]),type="l")
lines(xt, (yt[,1]+1.96*yt[,2]), lty=2)
lines(xt, (yt[,1]-1.96*yt[,2]), lty=2)
for (kk in (1:length(hh$breaks)-1)) {

```

A.1.2 Output From R

Call:

```
svyglm(formula = MAIS2p ~ Dv, design = dstrat, family = quasibinomial())
```

Survey design:

```
svydesign(id = ~1, weights = xt_sc, data = Data)
```

Coefficients:

```

      Estimate Std. Error t value Pr(>|t|)
(Intercept) -3.06577    0.44385  -6.907 4.40e-11 ***
Dv           0.05190    0.01203   4.315 2.33e-05 ***
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for quasibinomial family taken to be 1.042745)
Number of Fisher Scoring iterations: 4

```

A.1.3 OLC Calculation With Matlab

```

function [a_olc, vel_olc, dis_olc, time, timeAtCrit1, timeAtCrit2, warning, g_olc] =
OLC(CaseId, deltaV, time )
%OLC Summary of this function goes here
% Detailed explanation goes here
%only single impacts
%missing, when the crash is over
%missing if the case has 20 ms (getm se? thad eftir a, fam f? st?k)
vel=[0 deltaV*1.609*1000/3600]; %velocity in millimeters per milliseconds
time=[0 time'];
%OLC parameters
reldis1 = 65; % Slack displacement
reldis2 = 300; % Restraint displacement
g = 9.81e-3;

```

```

A0 = 0;
V0 = 0;
X0 = 0;
nrOfSamples = length(time);
%warning(1) indicates if slack displacement is not reached
%warning(2) indicates if Restraint displacement is not reached
%(equals 0 if reached 1 if not reached)
warning(1:2) = 0;
%Integration of velocity to displacement and differentiation to acceleration
V0 = vel(1);
A0 = (vel(2)-vel(1))/(time(2)-time(1));
acc(1) = A0;
dis(1) = X0;
for i=2:length(time)
    dis(i)=dis(i-1)+0.5*(vel(i-1)+vel(i))*(time(i)-time(i-1));
    acc(i)=(vel(i)-vel(i-1))/(time(i)-time(i-1));
end
%Get relative displacement and find the time for first relative displacement criteria
crit1=0;
crit2=0;
crit2IndexStart = nrOfSamples;
timeAtCrit1 = nan;
timeAtCrit2 = nan;
velAtCrit2 = nan;
for i = 1 : nrOfSamples
    deltax1(i)=dis(i)-V0*time(i);
    if deltax1(i)<=-reldis1 && crit1==0
        crit1=i;
        deltaInterp = [deltax1(crit1-1) deltax1(crit1)];
        timeInterp = [time(crit1 -1) time(crit1)];
        timeAtCrit1 = interp1(deltaInterp,timeInterp,-reldis1);
        crit2IndexStart = i;
        warning(1) = 1;
    end
end

% Reikna ut tima fyrir criteria 2
deltax2(1:nrOfSamples)=0;
if crit1==0
    crit2=nrOfSamples;
    time2=time(crit2);
    vel2=vel(crit2);
    % crit2Index=crit2IndexStart;
else
    for crit2Index = crit2IndexStart:nrOfSamples %took away +1
        if crit2==0
            deltax2(crit2Index)=deltax1(crit2Index)-1/2*(vel(crit2Index)-
V0)*(time(crit2Index)-timeAtCrit1);
            if deltax2(crit2Index)<=-reldis2;

```

```

        crit2=crit2Index;
        warning(2)=1;
        deltaInterp = [deltax2(crit2-1) deltax2(crit2)];
        timeInterp = [time(crit2 - 1) time(crit2)];
        velInterp = [vel(crit2 - 1) vel(crit2)];
        timeAtCrit2 = interp1(deltaInterp,timeInterp,-reldis2);
        velAtCrit2 = interp1(timeInterp, velInterp, timeAtCrit2);
        break
    end
end
end
end
if crit2==0
    crit2 = nrOfSamples;
end
%OLC acceleration of interpolated values
a_olc_m=(velAtCrit2-V0)/(timeAtCrit2-timeAtCrit1);
g_olc= (a_olc_m/9.81)*1000;
%Generate OLC time history
for i=1:length(time)
    if i<crit1
        a_olc(i)=0;
    end
    if i>=crit1
        if i<=crit2
            a_olc(i)=a_olc_m;
        end
        if i >crit2
            a_olc(i)=acc(i);
        end
    end
end
end
end
%Integration of OLC pulse to velocity and displacement
vel_olc(1)=V0;
dis_olc(1)=X0;
for i=2:length(time)
    vel_olc(i)=vel_olc(i-1)+0.5*(a_olc(i-1)+a_olc(i))*(time(i)-time(i-1));
    dis_olc(i)=dis_olc(i-1)+0.5*(vel_olc(i-1)+vel_olc(i))*(time(i)-time(i-1));
end
filename=[num2str(CaseId) '.mat'];
save(filename, 'a_olc', 'vel_olc', 'dis_olc', 'time', 'timeAtCrit1', 'timeAtCrit2', 'warning',
'g_olc')
end

```

A.1.4 MAIS Distribution for Each Year

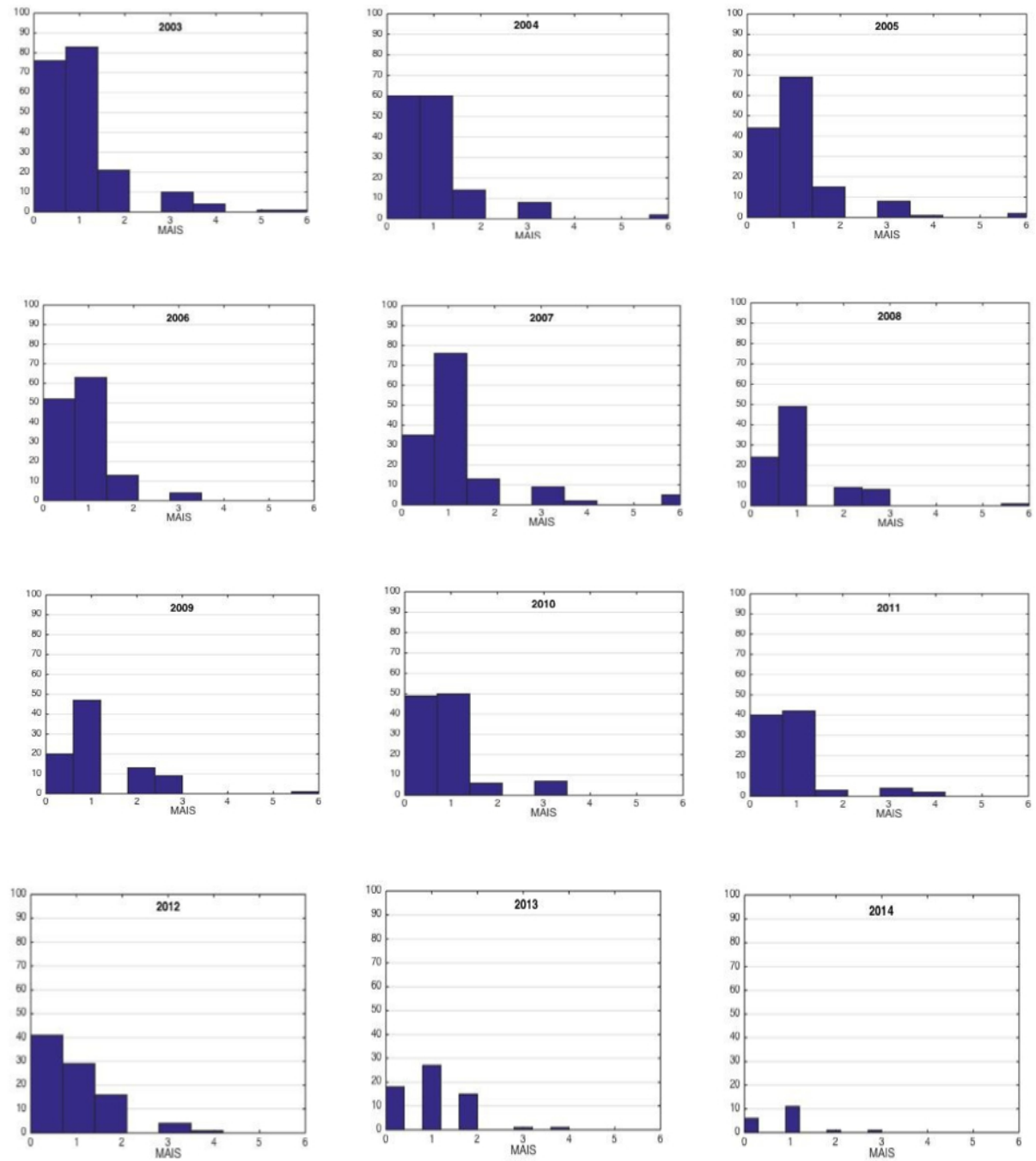


Figure A1 Cases for each year with MAIS distribution from 0-6 for all cases.

A.1.6 MAIS3+ and Chest Injury

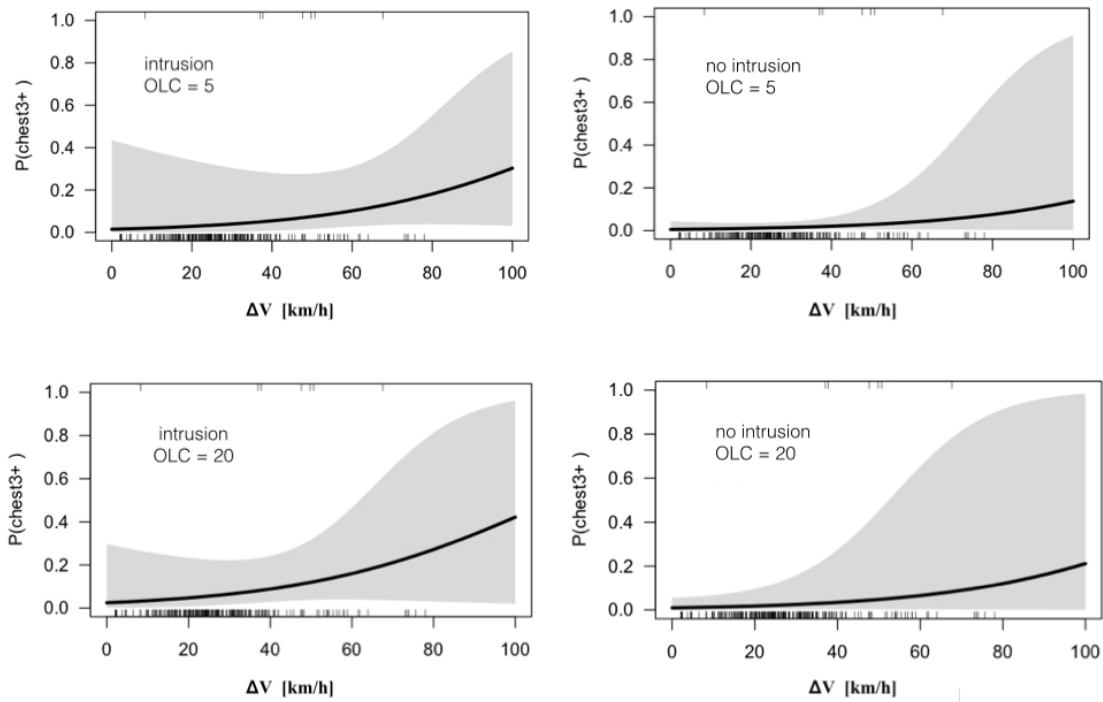


Figure A2 Injury risk curves with 95% confidence intervals estimated for the chest. The injury risk curve is plotted versus the longitudinal ΔV : Intrusion (left) and no intrusion (right).