Methodology for Determining Crash and Injury Reduction from Emerging Crash Prevention Systems in the U.S.

Kristofer Darwin Kusano

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Hampton C. Gabler, Chair
Stefan M. Duma
Warren N. Hardy
Michael L. Madigan
Miguel A. Perez

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ABSTRACT

In order to prevent or mitigate the negative consequences of traffic crashes, automakers are developing active safety systems, which aim to prevent or mitigate collisions. These systems are expensive to develop and as a result automakers and regulators are motivated to forecast the potential benefits of a proposed safety system before it is widely deployed in the vehicle fleet. The objective of this dissertation was to develop a methodology for predicting fleet-wide benefits for emerging crash avoidance systems as if all vehicles were equipped with a system. Forward Collision Avoidance Systems (FCAS) were used as an example application of this methodology.

The methodology developed for this research includes the following components: 1) identification of the target population, 2) development and validation of a driver model, 3) development of injury risk functions, 4) development of a crash severity reduction model, and 5) computation of fleet-wide benefits. This dissertation presents a general methodology for each of these components that could be used for any active safety system. Then a specific model is constructed for FCAS.

FCAS could potentially be applicable to 31% of all collisions, 6% of serious injury crashes, and 7% of fatal crashes. Annually, this accounts for 3.3 million collisions and 18,367 fatal crashes. We developed a model of driver braking in response to a forward collision warning. Next we used logistic regression to develop injury risk functions that predicted the probability of injury given the crash severity (ΔV) and occupant characteristics. Finally, we simulated 2,459 real-world rear-end collisions as if the driver had an FCAS with combinations of warnings, brake assist, and autonomous braking. We found that between 3.4% and 7.2% of crashes could be prevented and that many more could be mitigated in severity. These systems reduced the number of injured (MAIS2+) drivers in rear-end collisions between 32% and 55%. In total, the systems could prevent between \$184 and \$338 million in economic costs associated with crashes per year.

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Table of Contents

List of Figures

List of Tables

1. Background and Introduction

1.1. MOTIVATION

Societal costs from traffic crashes are a substantial burden to the world and U.S. economies. Worldwide there are an estimated 1.2 million road fatalities and between 20 and 50 million injuries caused by crashes per year [1]. In the U.S. there were 33,808 fatalities and approximately 2,217,000 injuries from traffic crashes in 2009 [2]. The total cost of crashes in the U.S., including loss of life, disability, and lost economic activity is estimated at upwards of $500 billion per year [3].

In the U.S. and many developed countries, there have been substantial improvements in vehicle design that have led to the reduction of fatalities and injury due to crashes over the last 50 years. In the U.S., fatal crashes are at their lowest absolute levels since 1966 when data was first collected even though the number of miles traveled on U.S. roads has increased substantially [2]. This drop in fatal crashes has been attributed to a number of engineering safety innovations introduced over time among other law and policy innovations. Seat belts are one of the most effective injury countermeasures and saved an estimated 13,250 lives in 2008 [4]. Seat belts were required to be fitted in all new vehicles starting in 1968 and states introduced legislation to require seat belt use while operating a vehicle in 1984. Air bags, another safety innovation, were required on new cars starting in 1997.

Safety systems have been traditionally categorized into two classes: active and passive safety systems. Active safety systems aim to prevent or mitigate the chance for the vehicle to be involved in a collision. Passive safety systems aim to prevent or mitigate negative consequences after a crash occurs. Restraint systems such as seat belts, airbags, and other innovations are examples of passive safety systems. Active safety systems include vehicle features like improved vehicle handling through radial tires and Anti-Lock Brakes (ABS) as well as newly emerging crash avoidance features discussed in detail below. In the early 1960's, Fritz Nallinger, member of the board of management for Diamler-Benz, described vehicle design activities as being either pertaining to primary and secondary safety [5]. He described primary safety as “the inherent driving safety of the vehicle, the driving safety resulting from simple vehicle handling and the driving safety brought about by the prevention of driver fatigue and driver distraction.” He described secondary safety as “all efforts which aim to prevent the physical and life-threatening consequences of an accident for all those involved or to reduce them to a minimum.” The use of the terms active and passive safety was first credited to the Italian engineer and writer Lugi Locati in 1964, and adopted by the “father of passive safety,” Diamler-Benz engineer Béla Barényi, and board member Hans Scherenberg in 1966 [6,7]. Barényi extended Locati’s definition of active safety to also include collision prevention systems [5,8]. The terms active and passive safety are now ubiquitously applied in the field of vehicle safety. Another category of safety design pertains to highway design and hardware, such as guardrail, to protect vehicle occupants [9-21].

Although passive safety has been very effective in reducing crash injuries, researchers, automakers, and governments have recognized that in order to further reduce the societal costs of crashes, systems must be developed that prevent crashes from ever happening. Systems are being developed and introduced by automakers today that are known as active safety systems, which focus on crash prevention and mitigation. In general, active safety systems assist the driver to control the vehicle so that collisions are avoided. Examples of active safety systems available on production vehicles include:

- Electronic Stability and Traction Control (ESC, ETC)
- Adaptive Cruise Control (ACC)
- Forward Collision Warning (FCW)
- Pre-crash Brake Assist
- Lane Departure Warning (LDW)
- Lane Keeping Assistance (LKA)
- Blind spot Monitoring and Prevention

Active safety systems are not a new concept but have only recently been available on production vehicles. Following meetings of the NATO Committee on the Challenges of Modern Society in 1969, a bilateral agreement between the U.S., French, German, Italian, United Kingdom, Japanese, and Swedish governments produced the Experimental Safety Vehicle (ESV) program [22]. The goal of this program was to develop experimental vehicles that focused on advanced safety systems and to hold international conferences to disseminate the knowledge related to these prototype vehicles. Initial ESV conferences focused on design of vehicle features such as crumple zones and three-point seat belts, not common in production vehicles at the time. As early as 1971, there were descriptions of Adaptive Cruise Control systems, which proposed similar radar sensors as those used in modern Forward Collision Warning systems [23]. The ESV conference continues today under the new name of the "International Conference on the Enhanced Safety of Vehicles."

Active safety systems are becoming available on more vehicles as either standard or optional equipment. Electronic Stability Control (ESC), which automatically modulates wheel torque to keep the vehicle from losing control, was required by law to be standard equipment on new vehicles manufactured starting September 1, 2011 [24]. Although not regulated, Forward Collision Warning (FCW) and Lane Departure Warning (LDW) systems are included in the U.S. New Car Assessment Program (NCAP), which assigns star safety ratings to new vehicles. FCW, a type of Forward Crash Avoidance System (FCAS), warns the driver of an impending frontal collision using radar or lidar technology to sense vehicles and/or objects in front of the equipped vehicle. LDW warns the driver of an unintended lane departure by tracking painted lane lines or road boundaries. LDW is typically implemented using cameras mounted on the vehicle.

Adoption of active safety systems is in the very early stages, and is relatively rare in the current U.S. vehicle fleet. It is estimated that only 15% of registered vehicles in 2010 had ESC as standard equipment, even though it has been offered on the U.S. market since the early 2000's and is now required on all new vehicles [25]. FCW is even less common. FCW was standard or optional equipment on only 1% of registered U.S. vehicles in 2010. The same figures are not available for other safety systems such as LDW or blind spot monitoring, but the proportion of vehicles with these systems today is expected to be similar to or less common than FCW.

Automakers and policymakers have several motivations to predict the societal benefits of proposed active safety systems before they are widely adopted. These systems require a large development investment cost for automakers. Therefore, automakers wish to pursue development on systems that will yield the most benefits. Although FCW and LDW are becoming available on more vehicles, they are still sold almost exclusively on luxury brands. One important decision automakers are facing today is whether to invest in developing these systems for their lower tier vehicles, which make up most of the vehicles on the road. Part of justifying this decision is an understanding of the safety benefits of a proposed system. Similarly, government organizations, such as the National Highway Traffic Safety Administration (NHTSA) in the U.S., are considering what, if any, regulation should govern these emerging systems. Any regulatory decision, e.g. requiring FCW or LDW on new vehicles similar to ESC, must be justified as having larger benefits than the cost of implementing the regulation. Research that attempts to predict what the potential safety benefits of these systems would be is central to these cost-benefit computations.

1.2. DESCRIPTION OF THE COMMON CRASH AVOIDANCE SYSTEMS

ESC, LDW, and FCAS are the three most common crash avoidance technologies offered on vehicles as evidenced by the regulation or inclusion of these systems in the NCAP program. In this section we will briefly describe the high-level functionality of these systems. These descriptions are based upon manufacturer descriptions of production systems. Systems vary by individual manufacturer, however.

ESC automatically controls the vehicle’s yaw rate to prevent the vehicle from entering a state of oversteer or understeer, as illustrated in Figure 1. Understeer and oversteering occur most often in either adverse road friction conditions or under steering inputs at high speeds. Most ESC systems control vehicle yaw rate by controlling the torque to individual wheels, either by braking or engine torque. The systems decide when to intervene by monitoring the yaw rate through a sensor placed on the vehicle and the steering wheel input. When the measured vehicle yaw rate deviates significantly from the expected vehicle yaw rate for a given steering input, ESC is activated.

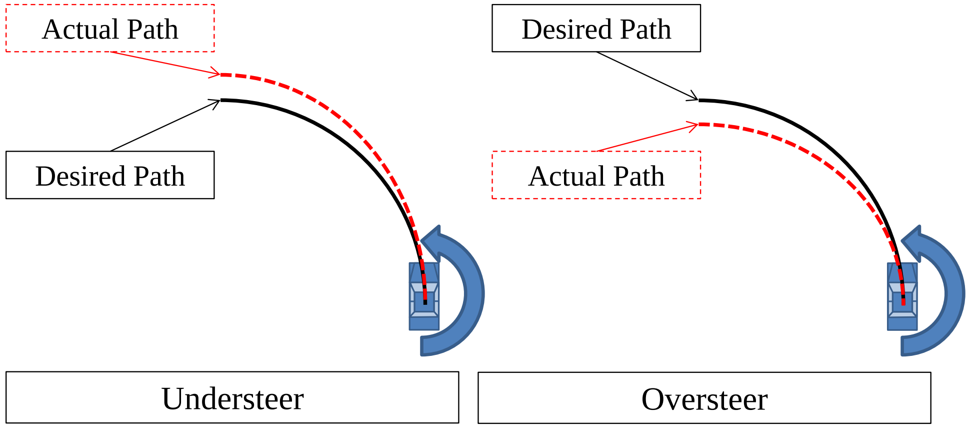


Figure 1. Electronic Stability Control (ESC) Modifies the Vehicle Yaw Rate to Prevent Understeer or Oversteer.

Forward Collision Avoidance Systems (FCAS) include several systems that can either prevent or mitigate frontal collisions. The most common are Forward Collision Warning (FCW), Dynamic Brake Assist (DBA), and Crash Imminent Braking (CIB). Figure 2 shows how these three components activate in the moments leading up to a frontal collision. FCW activates first to warn the driver of an impending collision. DBA is active starting at a threshold prior to the crash and increases the driver brake magnitude once the brakes are applied. CIB is autonomous and is the last system to activate and increases the braking force of the vehicle, even if there is no driver input. To sense vehicles in front of the equipped vehicle, these systems often use radar or lidar sensors because of their accuracy and large range. Some systems also use cameras mounted behind the windshield in place of or in addition to radar to further aid in object recognition.

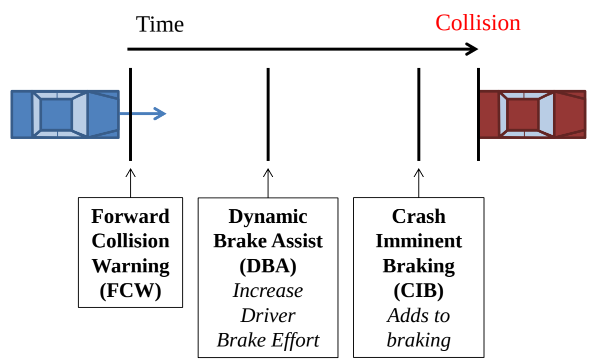


Figure 2. Activation of Forward Crash Avoidance Systems (FCAS) leading up to a Crash.

Lane Departure Warning (LDW) warns the driver of unintended lane departure events. Most systems detect when a vehicle is departing its lane by using a camera mounted behind the windshield to track lane lines on the road. A major limitation of current systems, therefore, is that they will not function in the absence of lane lines.

Another class of active safety systems are called Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) systems. These systems rely on wireless communication, called Dedicated Short Range Communication (DSRC), similar to the WiFi protocol between vehicles on the roads and static infrastructure, such as intersections. The application of V2V/V2I systems is use as a sensor in active safety systems. The information broadcast by these systems can be used in safety application such as ACC, blind spot monitoring, FCAS, and LDW. One advantage that V2V and V2I systems may have over systems that depend on other sensors, such as radar or vision, is that the wireless communications cannot be occluded by buildings, objects, or other vehicles. In intersection crashes, for example forward-looking sensors may not detect a vehicle traveling perpendicular to the equipped vehicle until it is too late to deliver an effective warning. The U.S. Department of Transportation's Research and Innovative Technology Administration (RITA) is currently funding the "Safety Pilot" program where thousands of vehicles in the Ann Arbor, MI area are being equipped with V2V and V2I systems [26].

1.3. PRIOR RESEARCH ON BENEFITS ESTIMATION OF ACTIVE SAFETY SYSTEMS

There has been prior research on the potential crash and injury prevention expected from proposed crash avoidance systems. In this section we briefly summarize major findings and methodologies from past studies on benefits estimation for ESC, FCAS, and LDW.

ESC was introduced earliest of these three active safety systems and is now equipped on a substantial number of vehicles in the U.S. As a result, the study of ESC effectiveness is a good example of the full life cycle of a safety system. Before the system is introduced on production vehicles, predictive methods must be used to estimate the expected benefits. After a system has been deployed in a sufficient number of vehicles, retrospective crash data can be used to derive the actual benefits of a system. For example, Farmer examined crash data from 10 states and found that the risk for being involved in a single vehicle crash was 41% lower for ESC-equipped vehicles than for vehicles without ESC [27]. Lie *et al.* performed a similar study using Swedish crash data and found ESC had an effectiveness of reducing all non-rear-end collisions by 16.7% and 21.6% for serious and fatal crashes, respectively [28]. A recent retrospective study of U.S. crash data found that approximately 863 lives were saved on U.S. roads in cars and light trucks in 2010 [29]. For a comprehensive review of ESC effectiveness from retrospective crash data, see Ferguson 2007 [29].

Unlike ESC, FCAS and LDW are just being introduced in the vehicle fleet. As a result, there are generally too few vehicles equipped with these systems to perform retrospective analyses on system effectiveness. One early retrospective study by Isaksson-Hellman and Lindman was able to determine that a Volvo FCAS system reduced insurance claims by 23% for a single vehicle model using Swedish data [31]. A similar study using insurance data as its source was performed by the Moore and Zuby of the Insurance Institute for Highway Safety [32]. They compared insurance claims costs for vehicles before and after they were available with FCW and LDW. They found a statistically signification decrease in overall insurance cost for vehicles equipped with FCW, but no difference for those equipped with LDW. One drawback of this methodology was that all insurance claims for the equipped vehicles were aggregated regardless of crash type. FCW and LDW will have little effect on the involvement of vehicles in crash types unrelated to their function. For example, it is unlikely that LDW will greatly modify the number of rear-end crashes a vehicle is exposed to. Therefore, this aggregated analysis does not predict how effective these systems are in the crash scenarios directly applicable to the systems' operation.

Due to the low market penetration cited earlier, these retrospective studies are still years away from being feasible in the U.S. in the same capacity as the ESC effectiveness studies cited above. Instead, most past studies pertaining to FCAS and LDW attempted to forecast the expected benefits of a system. A review of intelligent transport system effectiveness by Bayly *et al.* summarizes the results of studies of expected fleet-wide benefits for some proposed systems, including FCAS and LDW [33]. FCW systems were the most frequently studied FCAS component. Studies pertaining specifically to rear-end collisions reported a range of crashes prevented from as low as 7% to as high as 80%. Studies focusing on brake assist found a reduction in the number of applicable crashes from 26% to 75%. Benefits in these studies were often implied from an assumed proportion of a target population that would benefit from the FCAS component without considering the effectiveness of the systems on a case-by-case basis. Although every collision is different, these traditional effectiveness methodologies do not treat each collision individually and cannot predict the effectiveness of FCAS on a case-by-case basis.

Similar to FCAS effectiveness studies, LDW benefits studies often do not simulate individual collisions. For example, Abele *et al.* projected that LDW could reduce head-on and road departure crashes by 25% and reduce injury in these two crash types by 25% and 15%, respectively [34]. Their computations of benefits assumed that the system would provide the driver with a fixed amount of extra time to avoid the collision. They then statistically correlated this extra time to reduction in crash occurrence and severity.

Another source of benefits estimates is a NHTSA funded research program called the Advanced Crash Avoidance Technologies (ACAT) program. The ACAT program is a collaboration between NHTSA, automakers, and research institutions to develop what NHTSA has termed Safety Impact

Methodologies (SIMs) [35, 36]. Figure 3 shows the SIM framework proposed by NHTSA. The ACAT projects used this framework to create models of system performance and derived safety benefits using these models.

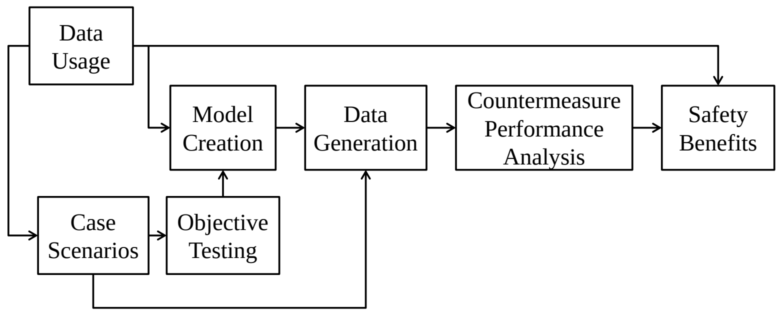


Figure 3. Schematic of NHTSA Safety Impact Methodology (SIM) Framework [35, 36]

The Honda/Dynamic Research Inc. (DRI) ACAT project predicted the benefits of a FCAS in rear-end collisions [37]. The approach of the project was to reconstruct individual crashes from a real-world crash database using dynamic simulation software, called PC-Crash. These baseline simulations were used to simulate the same crashes as if the vehicle was equipped with the FCAS. One drawback of this approach was that each crash reconstruction was labor intensive only allowing for approximately 100 simulations that were extrapolated to produce fleet-wide benefits. A similar case-by-case reconstruction approach was performed by Anderson *et al.* in Australia [38]. This study used the simulation software PreScan and found that 20% to 40% of fatal crashes and 30% to 50% of serious injury crashes would be prevented in target scenarios.

The Volvo/Ford/University of Michigan Transportation Research Institute (UMTRI) ACAT project predicted benefits of LDW [39]. This project also used dynamic vehicle simulations using the software CarSim to compare crashes with and without the proposed system. Instead of simulating individual crashes, distributions of the relevant parameters were fit to real-world crash data. The distributions included roadway, vehicle, environmental, and driver parameters that affect road departure crashes. Using these distributions, a Monte Carlo simulation approach was used where a large number of simulations were run drawing from these distributions. The aim of the Monte Carlo approach was to create a crash population that was similar to the actual crash population thus avoiding reconstructing individual crashes.

Driving simulators can also be used to assess potential benefits of collision avoidance systems. For example, Lee *et al.* exposed driving simulator users to a lead vehicle stopped scenario and found that FCW reduced the number of collisions for that scenario by 80.7% [40]. This and other driving simulator studies often only examine a small set of collision scenarios and thus it is difficult to derive the overall system benefits expected throughout the fleet. The focus of these simulator studies is often quantifying driver reaction times and input. In the current research, we will use driving simulator data as the basis for modeling a driver's reaction to a proposed system.

Naturalistic driving studies have also been used as the basis for benefits estimation. Naturalistic studies instrument personal vehicles and constantly record video and vehicle data over a long period of time. McLaughlin examined 13 rear-end and 70 near-crash events from the 100 Car Naturalistic study and simulated these events as if a FCAS was present [41]. This study found that between 50% and 70% of events could have been avoided. Naturalistic data are real-world crash events. With a large enough sample the crashes observed during such a study could be correlated to the driving population. One possible limitation is that crashes are relatively rare in these studies and as a result analysis of near-crash events is often used as a surrogate for crashes.

An advantage of using retrospective crash databases as the basis for benefits estimates is the large opportunity to study the number of serious crash events that can result in serious or fatal injury.

1.4. OVERVIEW OF PROPOSED RESEARCH

In this dissertation, I will present a research program that developed a methodology for determining societal benefits from new active safety systems yet to be widely deployed in the vehicle fleet. The objective of this method is to forecast the number of crashes and injuries that would be avoided if a proposed active safety system were to be deployed throughout the U.S. vehicle fleet. A focus of the proposed research was the simulation of real-world collisions on a case-by-case basis. Past studies often assumed overall system effectiveness and applied this effectiveness to all applicable cases macroscopically, ignoring the specifics of each crash. The current research performed "microscopic" simulations of individual cases extracted from real-world crash databases. This is challenging because of the lack of information present in these databases. Another unique goal of this approach is to be able to quickly simulate a large number of real-world crashes. Past studies have either painstakingly reconstructed and simulated a small population or used Monte Carlo methods as a surrogate for a population estimate. The current research will propose a method in which a large representative sample of collisions is able to be simulated given the operation of the system.

FCAS will be studied throughout this dissertation as an example system. The framework developed herein, however, can be readily adapted to predict benefits for other systems, such as Lane Departure Warning (LDW) systems or other proposed active safety systems.

Predicting societal benefits for such active safety systems has several tasks, each of which will be covered by a chapter of this dissertation, as shown in Figure 4. The tasks are: 1) identifying the target population, 2) developing a model of driver reaction to the system, 3) developing a model to predict injury reduction, and 4) developing a model for crash severity reduction with the system. These components rely on each other and can be combined to predict both the number of crashes and injury prevented by a proposed system.

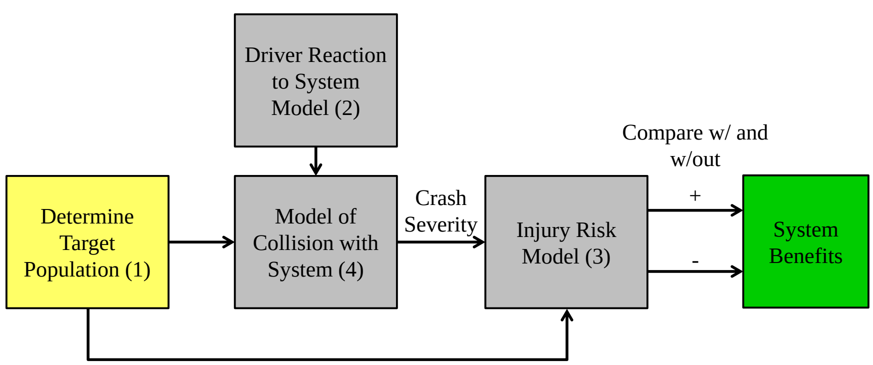


Figure 4. Method for Predicting Active Safety System Benefits

The target population for a system is the set of crashes in which a proposed system would most likely activate and mitigate or prevent the collision. For FCAS, the main crash scenario that would be mitigated or prevent is the rear-end collision, where the front of one vehicle contacts another vehicle traveling in the same direction and lane. In the proposed framework, the target population is determined from nationally representative crash databases, specifically the National Automotive Sampling System (NASS) for police reported crashes and the Fatality Analysis Reporting System (FARS) for fatal crashes. NASS and FARS are nationally representative crash databases funded by the National Highway Traffic Safety Administration (NHTSA).

Crashes investigated retrospectively rarely have the proposed active safety system. As a result, a method to model the driver's response prior to a crash as if the system were equipped is required. In the second task, we will both develop a model for driver reaction to an active safety system as well as propose a novel method for obtaining information on driver reaction, i.e. braking times, from Event Data Recorder (EDR) data. Experimental results from driving simulators or test tracks will also be used to develop such driver models. The proposed framework in this task includes a stochastic model to account for a range of driver reactions to the system by sampling from population distributions.

The hypothesis used in this framework is that the addition of an active safety system will mitigate the severity of a collision, or even prevent a collision, which will lead to a reduction in injury. In order to predict the reduction in injury expected from an active safety system, we developed a model that predicts injury outcome given a crash's severity. The model used in this framework was a binary logistic regression model that predicts the probability of a serious injury given the driver's seat belt use and the crash ΔV. ΔV (delta-V) is defined as the change of velocity of the vehicle during the crash and has been found to be highly correlated with injury outcome. The model was trained using NASS/CDS crashes that had injury outcome information as well as reconstructed crash ΔV.

Finally, we present a simulation model that predicts the reduction in severity in all applicable crashes with the proposed system and use the injury risk models developed in the previous task to predict system benefits. The core component of the crash severity reduction model is to predict a reduced ΔV after system activation given the original crash ΔV. This computation was developed for this project based on energy- and momentum-based crash reconstruction techniques similar to those used by the NASS/CDS investigators.

1.5. FRAMEWORK FOR COMPUTING SOCIETAL BENEFITS IN THE VEHICLE FLEET

The models described in the previous section can be used to predict benefits for a single crash. The goal of this work, however, is to predict fleet-wide benefits expected for the U.S. Using the models developed in the following chapters of this dissertation, the following framework will use the model outputs to compute expected benefits. This framework has the same general organization as many of the studies cited in the past works section, e.g. [35] and [36] from the ACAT research program. The SIM methodology introduced by NHTSA was formally defined by Burgett *et al.* [42].

The benefits of the system can be stated simply as

$$\text{Benefits} = \frac{\#\text{ without system} - \#\text{ with system}}{\#\text{ without system}} \tag{1}$$

where the number (# symbol) can represent the number of crashes, injuries, or fatalities. The number without the system is determined from the real-world data and the number with the system is the result of computational simulation.

The number of crashes with the system is found by summing over all crashes and unknowns:

$$\#\text{ Crashes with system} = \sum_{i=1}^{N} \sum_{j=1}^{M} w_i w_j f(\theta_i, \phi_j) \tag{2}$$

where N is the total number of collisions, M is the number of simulations representing different drivers per collision, $w_i$is the weight for the collision, w_j is the weight of the simulation, and $f(\theta_i, \phi_j)$ is the simulation result and has a value of 0 for a collision that is avoided and 1 for a collision that is not avoided. The driver reaction to a system in a retrospective crash database is unknown. As a result, in this framework each collision in a given dataset is simulated multiple times to account for unknowns. Using weights that describe how likely a driver reaction is, w_j, the expected number of collisions is aggregated by summing over all simulations. The simulation weight, w_j, is between 0 and 1. These weights can be derived from probability distributions of reaction times, for example. The total number of crashes in a population is then aggregated using a collision weight, w_i, that describes how likely a crash was to occur in the population. The case weight, w_i, is the number of similar collisions that exist in the population. Many nationally representative crash databases include case weights to account for uneven sampling of crashes.

The simulations have two types of input represented by the vectors θ_i and ϕ_j. θ_i is a vector representing the relevant road, vehicle, and occupant characteristics that are unique to each crash. This can include the roadway type, surface conditions, vehicle type, occupant age, and seat belt status. The data for θ_i is extracted from the real-world crash data and does not vary between simulations of a case. The vector ϕ_j represents the driver vehicle control characteristics that will affect the driver's response to a proposed system in the simulation. These factors can include what action the driver will take, e.g. brake or steer, driver reaction time, and driver input magnitudes.

Because the proposed method is based on simulation, a discrete number of simulations, M, and crashes, N, are summed. In a purely probabilistic method, both the summations would be replaced by integrals over some probability density functions that describe the distributions of crashes and driver reactions, respectively. However, such distributions are often intractable because of complex interactions between crash variables. The proposed method is both probabilistic and computational in that it simulates all cases in a target population and weights these simulation results to represent the true distribution of crashes. The crash and injury outcomes are computed using computational models.

The number of injuries expected with a system is not only a function of whether a crash occurs or not but also the severity of the crash if it does occur:

$$\text{\# Injuries with system} = \sum_{i=1}^{N}\sum_{j=1}^{M} w_i w_j g(\theta_i, \gamma_j) \tag{3}$$

where $g(\theta_i, \gamma_j)$ is an injury risk function that describes the probability of an injury occurring given some or all the crash conditions in θ_i and a crash severity measure, γ_j. Common crash severity measures are impact speed of the vehicle or change in velocity during the impact, ΔV. In the proposed framework severity is also determined from simulation and is a function of the initial conditions of the crash (θ_i) and the driver input (ϕ_j). Equation 3 uses the same case and simulation weights as equation 2.

2. Pre-crash Scenarios for Determining Target Populations of Active Safety Systems from Retrospective Crash Databases

2.1. ABSTRACT

The objective of active safety systems is to prevent or mitigate collisions. A critical component in the design of active safety systems is to identify the target population for a proposed system. The target population for an active safety system is that set of crashes that a proposed system could prevent or mitigate. Target crashes have scenarios in which the sensors and algorithms would likely activate. For example, the rear-end crash scenario, where the front of one vehicle contacts another vehicle traveling in the same direction and in the same lane as the striking vehicle, is one scenario for which Forward Collision Warning (FCW) would be most effective in mitigating or preventing. This paper presents a novel set of pre-crash scenarios based upon coded variables from NHTSA's nationally representative crash databases. Using three databases the scenarios developed in this study can be used to quantify the number of police reported crashes, seriously injured occupants, and fatalities that are applicable to proposed systems. In this paper, we use the pre-crash scenarios to identify the target populations for FCW, Lane Departure Warning (LDW), and Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) systems. This study found that these active safety systems could potentially mitigate approximately 1 in 5 crashes in the U.S., including serious injury and fatal crashes. Annually, this corresponds to 1.1 million all severity, 14,435 serious injury (MAIS3+), and 6,352 fatal crashes.

2.2. INTRODUCTION

The target population for an active safety system is that set of crashes that a proposed system could prevent or mitigate. These crashes have scenarios in which the sensors and algorithms would likely activate. For example, the rear-end crash scenario, where the front of one vehicle contacts another vehicle traveling in the same direction and in the same lane as the striking vehicle, is one scenario in which a Forward Collision Avoidance System (FCAS) would activate. Many FCAS systems utilize forward-facing sensors, e.g. radar. Because the leading vehicle is in view of the sensors prior to the crash, rear-end collision are likely to be detected. In other forward crash scenarios, such as intersection or turning crashes, a struck vehicle may come into view of the sensors too late to activate. This is especially true for the warning component, which needs longer times to be maximally effective.

Another important aspect of the target population is the societal cost which a proposed active safety system could potentially mitigate. These societal costs of crashes can be measured by the costs associated with injured occupants including the costs of medical treatment, lost wages, and long-term disability. Because active safety systems have tremendous equipment and development costs for automakers, the systems that can potentially mitigate the most injuries should be prioritized based on cost reduction.

An important tool in identifying target populations for countermeasures is examining the crash population in terms of crash scenarios. Crash scenarios group similar crashes in real-world crash databases using the variables coded for each case. Previous researchers have developed crash scenarios for nationally representative crash databases, such as those by Eigen and Najm [43]. The approach in Eigen and Najm was to use variables that described the pre-crash phase of the collision to group scenarios. We will adapt these scenarios for the current study and use them to examine the target population of forward collision avoidance systems as an example.

The objective of this study is to develop crash scenarios for use in identifying the target population for active safety systems.

2.3. METHODOLOGY

2.3.1. Data Sources

Four data sources were used for this study: the National Automotive Sampling System (NASS) General Estimates System (GES), the NASS Crashworthiness Data System (CDS), and the Fatality Analysis Reporting Systems (FARS), and the National Motor Vehicle Crash Causation Survey (NMVCCS). GES is a representative sample of all police reported crashes in the U.S. CDS is a representative sample of crashes which involve passenger vehicles towed from the scene due to damage. FARS is a census of all traffic related fatalities in the U.S. NMVCCS was a special study that focuses on collecting critical factors that lead to collision, such as distraction, close following distance, etc. All four databases are funded and maintained by the National Highway Traffic Safety Administration (NHTSA) and are released to the public on an annual basis, except for NMVCCS which was conducted between years 2005 and 2007.

Each database represents a different population of crashes. The GES sample is an estimate of all crash exposure in the U.S. There are approximately 50,000 crashes per year that make up the GES sample. The CDS database is similar, but is restricted to tow-away crashes only. Unlike GES that collects data from police accident reports only, CDS has trained crash investigation teams that gather in-depth information on each crash. The CDS investigators photograph and diagram the crash scene, prepare scene diagrams, measure vehicle damage, conduct interviews with occupants involved, and collect injury information from medical sources. FARS is similar to GES in that most of the data is gathered from police accident reports. GES and CDS are probability samples of police reported crashes that are weighted to represent all crashes. FARS is meant to be a census of all fatal traffic crashes.

Because these three data sources are all maintained by NHTSA, some of the key variables are similar. Of interest when defining pre-crash scenarios are those coded variables that pertain to the pre-crash period of the event. In the last several years of data collection, i.e. 2010 and 2011, the pre-crash variables in GES and FARS have been standardized so that they match the CDS definitions [44]. The standardization of these pre-crash variables across all three databases allows for the comparison of these data sources. Such a comparison prior to year 2010 would have not been possible. For this study, the last 5 years of NASS/CDS (2007 to 2011) were used. For GES and FARS years 2010 and 2011 were used. Previous years of FARS and GES either do not have pre-crash variables or they were drastically changed for the 2010 standardization and could not be used for this study. In order to be included in the CDS database, at least one passenger vehicle must have been towed from the scene due to damage. To facilitate comparisons between data sources, cases from FARS and GES were restricted to those involving at least one passenger vehicle. The variable definitions for passenger vehicles, including cars, light utility, light vans, and light trucks, are included in the appendix.

Active safety systems, such as FCAS, Lane Departure Warning (LDW), and Vehicle-to-Vehicle (V2V) systems, all are driver assistance systems. These systems main contribution is returning the drivers attention to the road and then assisting the driver in avoiding a collision. As a result, those collisions that are caused by driver inattention, as opposed to other causes like excessive speed, may stand to benefit the most from active safety systems. Critical reasons for collisions are not consistently collected in the GES, CDS, or FARS. Police jurisdictions, which generate the police accident reports that make up the bulk of the collected data, have only recently started to collect information related to potential distraction prior to crashes. NMVCCS is a unique dataset in that its focus is crash causation. To aid in this study, one requirement to be included in NMVCCS was that the crash investigator had to arrive at the scene of the crash before emergency personnel cleared the crash scene. This allowed the investigators to question first responders, occupants, and witnesses to better understand the contributing factors that caused the crash.

The data are provided by NHTSA to the public via download (ftp://ftp.nhtsa.dot.gov/). Files are sometimes modified from their original release, to correct mistakes in the data. GES 2010 files were dated October 11, 2011 and 2011 files were dated December 9, 2012. CDS 2007 files were dated August 15, 2008, 2008 files were dated December 1, 2011, 2009 files were dated September 20, 2010, 2010 files were dated September 11, 2011, and 2011 files were dated December 18, 2012. FARS 2010 files were dated July 31, 2012 and 2011 files were dated August 14, 2012. The NMVCCS file was dated July 20, 2008.

2.3.2. Crash Scenarios

Figure 5 shows photographs taken as part of a fatal rear-end collision involving a 2010 Ford Fusion (right of Figure 5) which struck a 2007 Subaru Impreza (left), which was stopped in traffic. The case was investigated as part of the CDS database. This case is an example of a crash that would be applicable to FCAS. The driver of the Impreza, a 37-year-old male, was fatally injured (brain stem transection) while a 3-year-old female in a child seat in the middle position of the back seat only suffered moderate injuries (a foot fracture and lung contusion). The driver of the Fusion was a 49-year-old male who had a 0.0 blood alcohol concentration as measured by a police administered test. The driver of the striking vehicle was seriously injured with bilateral rib fractures that required a 9-day hospitalization.

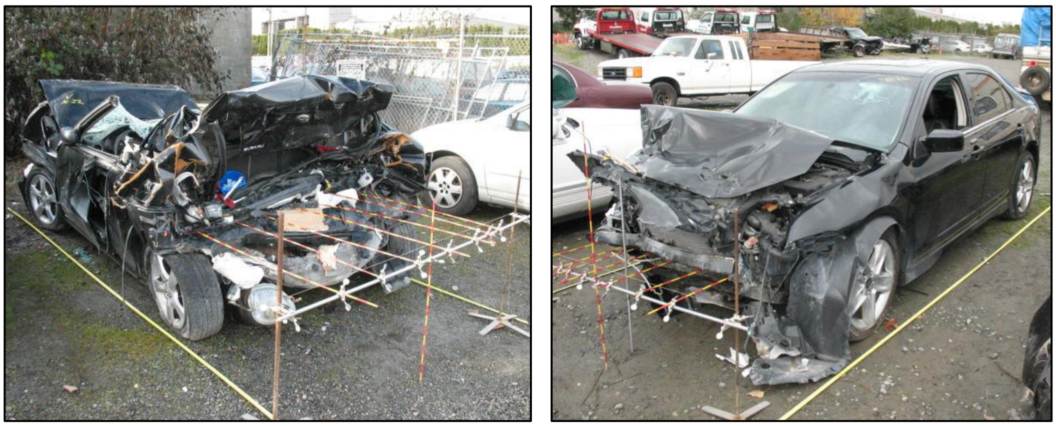


Figure 5. Photograph from NASS/CDS Investigation of a Fatal Rear-end Collision (Case 2010-82-137).

In the NHTSA databases, the critical pre-crash event, pre-crash movement, and accident type variables provide information about the configuration and driver maneuvers prior to each crash. Figure 6 shows the approach developed for this study to classify collisions using database variables. Example values for each variable are provided below for the striking vehicle of the rear-end crash shown above. The critical pre-crash event is the event that made the crash imminent as determined by the investigator. The databases in our study had 92 critical event categories. The accident type variable describes the configuration of the crash for the first harmful event and has approximately 100 values. Finally, the pre-crash movement describes the vehicle's activity prior to the crash, such as decelerating in lane, passing, or going straight. Together these three variables were used to assign every vehicle in each database a pre-crash scenario. All crashes in the database were assigned a single crash scenario. Each crash was assigned a scenario based upon the crash scenarios of the two vehicles involved in the first harmful event in the crash. If there was only one vehicle involved in the crash, this vehicle was used to determine the scenario.

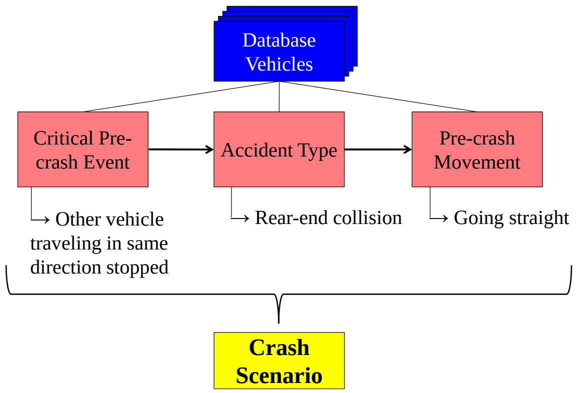


Figure 6. Approach for Determining Pre-Crash Scenario from NASS/CDS Variables.

In many cases the critical pre-crash event and accident type variables indicate very similar information, such as in the example rear-end crash above. The accident type variable must correspond to the first impact in a crash whereas the critical pre-crash event describes what made the first pre-crash event unavoidable. In some scenarios this can lead to meaningful differences with regard to if an active safety system would activate. Consider NASS/CDS case 2011-41-116 whose scene diagram is shown in the left of Figure 7. Vehicle 1, a 2001 Mercedes Benz E-class departed its lane and struck vehicle 2, which was stopped. The pre-crash critical event for the striking vehicle was “this vehicle traveling over the left lane line” and the accident type was a rear-end collision. The pre-crash maneuver of the striking vehicle was going straight, not changing lanes or avoiding another critical event. For the study of active safety systems, this crash would most likely be mitigated by a Lane Departure Warning (LDW) system that could have warned the driver he was exiting his lane.

Compare this rear-end crash with the one involving the Fusion and Impreza, shown in the right of Figure 7. FCAS could more likely be applicable to this crash because the struck vehicle would have been in view of the front-facing sensors in time to either deliver a warning or take action. In our approach to assign pre-crash scenarios, pre-crash critical event was prioritized over accident type because it described the portion of the pre-crash phase where active safety systems would activate more completely.

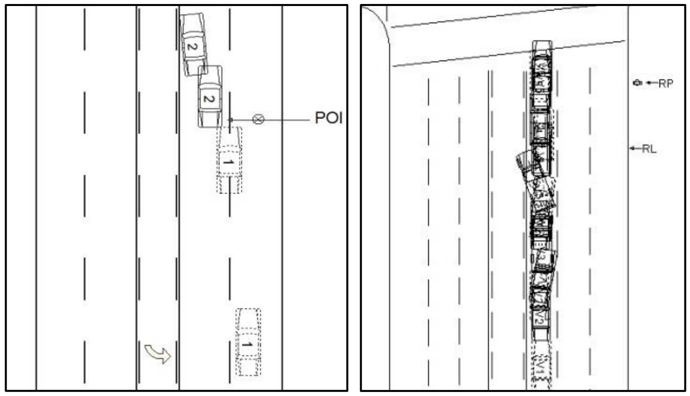


Figure 7. Scene Diagram Prepared by Investigator for NASS/CDS Cases 2011-41-116 (Left) and 2010-82-137 (Right).

Figure 8 shows the single vehicle crash scenarios: single vehicle crashes with fixed objects on the roadside, control loss, animal in the road, pedestrian or cyclist in the road, object in the road, and other. Similarly, scenarios for multiple vehicle collision are shown in Figure 9. For target population analysis, many of these crashes can be broken down further into subgroups based on pre-crash maneuver (e.g. turning, going straight) or by object struck.

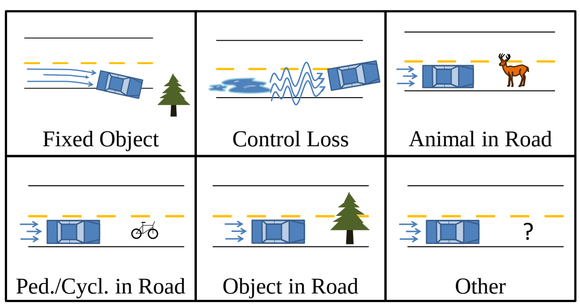


Figure 8. Single Vehicle Crash Scenario Categories.

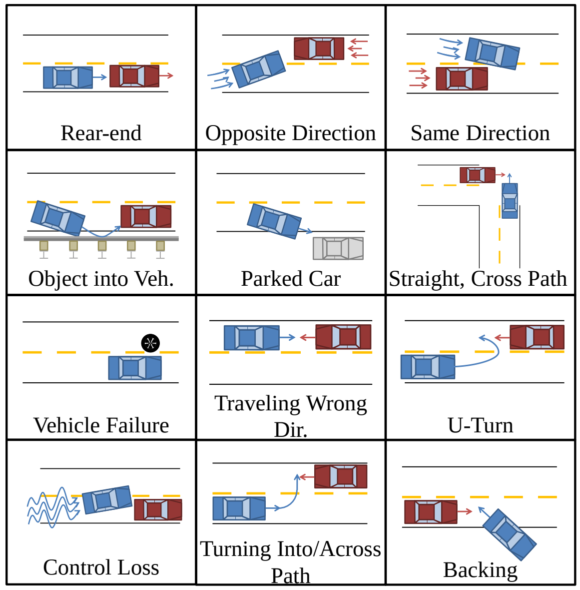


Figure 9. ***Multi-Vehicle Crash Scenario Categories.***

2.3.3. Measure of Injury and Harm

In addition to examining the frequency of crashes, the number of injuries is also an important measure of the target population. NASS/CDS codes individual injuries using the Abbreviated Injury Scale (AIS). The AIS is a one to six score that measures the threat to life an injury poses [45]. A score of one corresponds to a minor injury and a score of six corresponds to an unsurvivable injury. NASS/CDS includes AIS codes for each injury suffered by occupants. AIS scores are derived from medical records and coded by a trained AIS coding specialist. Other crash databases, such as GES, often use less exact injury scales, e.g. the KABCO scale, that are designed to be assigned by non-medical staff, e.g. police officers filling out police accident reports. These less exact injury measures assign either no injury, possible injury, moderate injury, incapacitating injury, or fatal injury to each occupant. This assessment is often made at the crash scene, is not based on medical records, and is therefore less reliable [46].

In this study a serious injury to a body region was considered as those with AIS level 3 and above (AIS3+). Occupants were considered seriously to fatally injured if the maximum of their body region AIS (MAIS) was of level 3 or greater (MAIS3+) or if the occupant was fatally injured. The AIS is a threat to life scale. Another measure, known as Harm, attempts to place a socioeconomic cost on injuries sustained from a crash. The Harm metric is based on medical costs, lost wages, and long term disability from an injury and is often measured with a monetary value. Each body region (e.g. head, chest, lower extremity) is assigned a representative cost for each AIS level of injury. Next, the costs of all injuries to an occupant are summed to find the Harm cost of a crash. In this study we used Harm values presented by Fildes *et al.* [47-49].

2.3.4. Critical Reason in NMVCCS Crashes

Each crash in NMVCCS was assigned a critical reason by the investigators. The critical reason is defined as the factor that most contributed to the crash occurring and is often the last event in the causal chain that lead to the crash being unavoidable. The critical reason coded by the NMVCCS investigator could be assigned to one of 67 reasons for each vehicle involved in a crash. To simplify presentation of these categories, the 67 reasons were reduced to 11 categories by grouping similar critical reasons [65, 66]. Examples of the critical reasons in each of the 11 categories are tabulated in Table 1.

2.3.5. Target Populations for Active Safety Systems

The target population for an active safety system is the set of collisions that would be most likely mitigated by a system. In this study we examined the target populations for several systems becoming available or being developed: Forward Collision Warning (FCW), Lane Departure Warning (LDW), and Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) systems. FCW and LDW warn drivers of impending frontal collisions and inadvertent lane departures, respectively. FCW and LDW are available as optional or standard equipment on many production vehicles. V2V and V2I are communication systems where vehicle safety data, e.g. position, speed, and heading, are shared between vehicles and infrastructure. This information can be used in safety applications similar to FCW and LDW. One advantage of V2V and V2I is that they are not restricted by line of sight of the sensors. FCW use radar and/or cameras to sense other vehicles and LDW systems often use cameras to track lane lines. The systems will fail if the objects being tracked are occluded, such as in intersection situations.

Table 1. Examples of Critical Reasons Categories from NMVCCS Coded Critical Reason.

Derived Category	Example (critical reason from NMVCCS)
Non-Performance Error	Sleeping
	Heart attack or other physical impairment
	Other Critical Non-performance
Distraction	Inattention (i.e. daydreaming)
	Internal Distraction
	External Distraction
	Inadequate Surveillance
Speed Related	Too fast for conditions
	Too fast to respond
	Too fast for curve/turn
Judgment Error	Misjudged gap or other's speed
	Following too Closely
	False Assumption of Other's Actions
Illegal Maneuver	e.g. Illegal Passing, turned from wrong lane
Aggressive Acts	Rapid/Frequent Lane Change, Rapid Accelerating, Obscene Gestures
Inadequate Evasive Maneuver	Inadequate Action (e.g. braking only)
	Incorrect Action
Performance Error	Panic/Freeze
	Overcompensation
	Poor Direction Control
Vehicle Failure	Brakes Failed
	Tires/Wheels Failed
	Steering Failed
	Transmission/Engine Failure
	Cargo Shifted
Highway Conditions	Signs/Signals Missing
	View Obstructed by Road Design
	Maintenance Problems
	Slick Roads
Environmental Conditions	Rain, snow
	Fog
	Glare
	Blowing Debris

Table 2 summarizes the applicable crash scenarios for each of these systems. Rear-end collisions, where the driver was not maneuvering before the crash, are the most applicable scenario for FCW. The vehicles in front of the equipped vehicle must be tracked well before the crash in order to deliver an effective warning. This is the case in rear-end collisions but might not be true for crash scenarios such as opposite direction crashes. LDW is applicable to road departure, opposite direction, and same direction crashes when the driver of the departing vehicle is lane keeping, i.e. going straight, prior to the departure.

V2V and V2I systems could mitigate intersection and turning crashes. Drivers could be warned if they are about to enter an intersection at the same time as another vehicle as well as advise drivers when it is safe to turn across opposing lanes of traffic. V2V could also be used to accomplish the same goals as FCW. Rear-end crashes were not included in the V2V/V2I target population so that the systems' target populations are mutually exclusive.

Table 2. Applicable Crash Scenarios for Three Active Safety Systems

System	Crash Scenarios
Forward Collision Warning (FCW)	• Rear-end, no maneuvers
Lane Departure Warning (LDW)	• Road departures, lane keeping • Opposite direction, lane keeping • Same direction, lane keeping
V2V/V2I	• Straight crossing paths (SCP) • Left turn across path, Opposite Direction (LTAP/OD) • Left turn across path, Perpendicular • Turn into path, Same Direction

The crash scenarios are only part of identifying the target population for active safety systems. As mentioned previously, the active safety systems listed above will be most effective in mitigating crashes where the driver of the striking vehicle is distracted. We adjusted our target population estimates derived from GES, CDS, and FARS by assuming the proportion of distracted drivers in these databases would be similar to crashes from NMVCCS.

2.4. RESULTS

2.4.1. Selected Cases

Table 3 shows the number of crashes from GES, CDS, and FARS. GES and CDS are weighted samples of crashes. Each crash in the database is assigned a weight that describes the number of similar collisions that occurred nationally during the sample time. On average, there were 5.2 million police reported crashes, 2.1 million tow-away crashes, and 28,373 fatal crashes per year involving at least one passenger vehicle. The total number of involved occupants, both in motor vehicles and non-motorists, was tabulated from all GES crashes. There were approximately 37.6 million persons exposed to traffic related crashes involving at least one passenger vehicle per year. The number of seriously injured occupants (MAIS3+) was tabulated from CDS and totaled approximately 70,129 persons per year. There was an average of 30,960 fatalities annually, tabulated from FARS. NMVCCS was collected from July 1, 2005 to December 31, 2007, which corresponds to approximately 2 years and 7 months.

Table 3. Number of Crashes and Persons involving at least one Passenger Vehicle from GES 2010-2011, CDS 2007-2011, FARS 2010-2011, and NMVCCS 2005-2007

	Total		Annual Average	
Category	**n**	**Frequency**	**n**	**Frequency**
GES Crashes	97,975	10,404,563	48,988	5,202,281
CDS Crashes	24,464	10,267,849	4,893	2,053,570
FARS Crashes	56,745	56,745	28,373	28,373
NMVCCS Crashes	5,470	2,188,970	2,115	846,437
Total Occupants (GES)	652,854	75,239,504	326,427	37,619,752
MAIS3+ Occupants (CDS)	4,733	350,645	947	70,129
Fatalities (FARS)	61,919	61,919	30,960	30,960

NASS/CDS focuses on crashes that involve injury that occurs to passengers in motor vehicle crashes. Because at least one passenger vehicle must have been towed from the scene due to damage in NASS/CDS cases, there are very few crashes that involve non-motorists, i.e. pedestrians and cyclists. Crashes involving a vehicle and pedestrian are particularly harmful [50-53]. Motorcycles are included in NASS/CDS and are at particular risk for serious injury or fatalities [54-64]. Also excluded are single vehicle crashes that do not involve passenger vehicles. To aid comparison with CDS, GES and FARS were restricted to crashes involving at least one passenger vehicle. This restriction accounted for 96% of GES crashes and 94% of FARS crashes. All cases in NMVCCS also involved at least one passenger vehicle.

Figure 10 shows the number of occupants (GES), seriously injured (MAIS3+) occupants (CDS), and fatalities (FARS) for single and multiple vehicle crashes. Only 20% of occupants were involved in single vehicle crashes, yet 46% of seriously injured occupants and 56% fatalities were in single vehicle crashes. Approximately 43% of Harm was in single vehicle crashes, which agrees with the number of seriously injured drivers. Of fatal single vehicle crashes, however, almost 1 in 5 were vehicles striking pedestrians or cyclists, almost all of which were fatalities involving occupants not in a motor vehicle. Of all fatalities, 45% were single vehicle crashes excluding pedestrian and cyclist crashes, almost equaling the proportion of seriously injured occupants involved in single vehicle crashes.

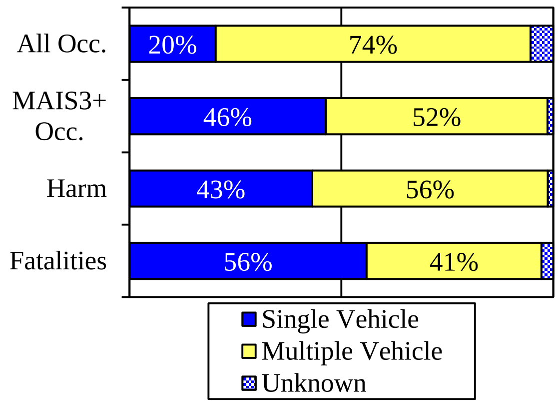


Figure 10. Number of Occupants, Seriously Injured (MAIS3+) Occupants, and Fatalities in Single and Multiple Vehicle Crashes involving at least one Passenger Vehicles.

2.4.2. Active Safety Systems in the Vehicle Fleet

FCW and LDW systems are relatively new systems that have not been widely adopted in the fleet. Starting with model year 2011, the New Car Assessment Program (NCAP) added the presence of FCW and LDW on a vehicle as part of their evaluations of vehicles. In order to claim that a vehicle has FCW or LDW, the vehicle must pass a confirmation test track test. The NCAP evaluations for FCW and LDW were started with model year 2011 vehicles and at the time of writing contain vehicle model years through 2013.

The FCW confirmation test is composed of a lead vehicle stopped, lead vehicle deceleration, and lead vehicle moving at a lower constant speed, summarized in Table 4 [67]. Each scenario is run seven times and the vehicle passes the confirmation test if 5 out of 7 of the trials for each scenario successfully deliver a FCW. In addition, no two trials may result in failure in a row for a scenario. Success is determined if an audible, visual, and/or haptic warning is delivered before Time to Collision (TTC) warnings. The TTC is the instantaneous time until a collision occurs. The FCW confirmation test computes TTC using the speed of the subject vehicle, the speed of the lead vehicle, and the deceleration of the lead vehicle.

Table 4. Forward Collision Warning Confirmation Test Scenario Procedures [67].

Test	Subject Vehicle (mph)	Lead Vehicle Speed (mph)	TTC at Least (s)	Trials
1	45	0	2.1	7
2	45	45, 0.3 g braking	2.4	7
3	45	20	2.0	7
Total				21

The LDW confirmation test is run on a test track with a single lane marking painted on the surface [68]. The vehicle is driven at 45 mph and a test driver manually steers the vehicle over the lane line with a vehicle speed perpendicular to the lane marking between 0.1 m/s to 0.6 m/s (0.5 m/s nominal value). These tests are conducted to the left and right side of a lane marking with different compositions, as shown in Table 5. Botts Dots are a raised retroreflective marking used in some states, such as California, that are considered difficult for the visions systems to detect. In total, 30 trials are run. The vehicle passes the confirmation test if 3 out of 5 trials for each scenario are considered passing and 20 out of 30 overall tests are considered passing. Each trial is considered a pass if an audible, visual, or haptic LDW is delivered before the leading point of the vehicle has traveled 0.3 m past the lane line. One potential weakness of the proposed test methodology, however, is that the speeds and angles in the test may be much lower than those experienced in real-world road departure crashes [69].

Table 5. Lane Departure Warning System Confirmation Test Scenarios [68].

Line Type	Departure Direction	Number of Trials
White Solid	Left	5
	Right	5
Yellow Dashed	Left	5
	Right	5
Botts Dots	Left	5
	Right	5
Total	-	30

The NCAP publishes results of its evaluations for new vehicles on its website, safercar.gov, for consumers. By matching the makes and models of the vehicles tested for NCAP to GES, CDS, and FARS, we can estimate approximately how many vehicles could be equipped with these systems. Table 6 lists the vehicle makes and models that have FCW or LDW as determined by the NCAP confirmation tests. All vehicles that have FCW or LDW offer the systems as optional equipment, that consumers must purchase on top of the cost of the vehicles. The only exception was the 2013 Honda FCX, which had LDW as standard equipment. Most makes and models that offer FCW or LDW are luxury brands, e.g. BMW, Mercedes-Benz, Audi, Infiniti, Cadillac, Lincoln, and Volvo. There are a few, however, high volume vehicles that now have FCW or LDW, e.g. Dodge Durango; Jeep Grand Cherokee; Ford Edge, Explorer, Flex, and Taurus; Chevrolet Equinox and Malibu; Honda Accord and Civic. To be included on this list the vehicles must have been tested by NHTSA's NCAP test track methodology discussed previously. Vehicles not included in this list may currently offer systems that are similar to the specifications of the NHTSA FCW and LDW. For example, the Toyota Prius offers a "Pre-Collision System" and "Lane Keeping Assist," but did not meet the requirements for the NCAP test.

Safety features introduced on new vehicles today can take many years to penetrate the vehicle fleet. Figure 11 shows the cumulative distribution of model years of passenger vehicles from GES, CDS, and FARS. The distributions are similar, with median model years of 2002, 2001, and 2001 for GES, CDS, and FARS, respectively. The 2011-2013 vehicles tested as part of NCAP make up only 2.5% of GES, 0.7% of CDS, and 1.6% of FARS. Because the newest years of data available are 2011, there were no 2013 model year vehicles in the samples.

Table 6. List of Vehicles with FCW or LDW as Optional Equipment according to NCAP 2011-2013

Model Year Range Tested	Make	Model Class/Models Tested	FCW Optional	LDW Optional
2013	Audi	A4, A5, A6, A7, A8, A8L, Allroad, Q5, Q7, RS5, S4, S5, S6, S7, S8	Yes	No
2013	Bentley	Continental Supersports	Yes	Yes
2013	Rolls-Royce	Ghost EWB	Yes	Yes
2011-2013	BMW	528i, 535i/GT/xDrive/xDrive GT, 550i/GT/xDrive/xDrive GT, X5 xDrive35i/xDrive 35d/xDrive50i, X6 xDrive35i/xDrive50i, 740i/Li, 750i/Li, 750i/Li xDrive, 760i/Li	Yes, Except[1]	Yes
2012-2013	BMW	528Xi, 640i, 650i/Xi, 750Li, Active Hybrid 740Li/750i/750Li	Yes, Except[2]	Yes
2013	BMW	328/335i xDrive, X3 xDrive28i/xDrive35i, 528i xDrive, M5, X5 M, X5 xDrive50i, 640i/650i Gran Coupe, 650i xDrive Gran Coupe, M6, Active Hybrid 3/535i	Yes	Yes
2013	BMW	Active Hybrid 750i, Active Hybrid 750Li	Yes	No
2012-2013	Chrysler	300	Yes	No
2012-2013	Dodge	Charger, Durango	Yes	No
2013	Dodge	Charger Pursuit	Yes	No
2011-2014	Jeep	Grand Cherokee	Yes	No
2011-2013	Ford	Edge, Explorer	Yes	No, Except[3]
2013	Ford	Flex, Taurus	Yes	No
2013	Ford	Fusion, Fusion Hybrid	Yes	Yes
2011-2013	Lincoln	MKX	Yes	No
2013	Lincoln	MKS, MKT, MKZ HEV	Yes	Yes
2012-2013	GMC	Terrain	Yes	Yes
2012-2013	Chevrolet	Equinox	Yes	Yes
2013	Chevrolet	Malibu, Volt	Yes	Yes
2011	Buick	Lucerne	No	Yes
2013	Cadillac	ATS, XTS	Yes	Yes
2011	Cadillac	DTS, STS	Yes	Yes
2013	Honda	FCX (hydrogen vehicle)	Yes[4]	Yes
2012	Honda	FCX (hydrogen vehicle)	Yes[4]	No
2013	Honda	Accord, Civic Hybrid	Yes	Yes
2011-2013	Acura	MDX	Yes	No
2011-2012	Acura	ZDX	Yes	No
2011	Acura	RL	Yes	No
2011-2013	Hyundai	Equus, Genesis	No	Yes
2011-2013	Infiniti	FX50, M37, M56	Yes	Yes
2012-2013	Infiniti	QX56, EX35, FX35, M35 HEV	Yes	Yes
2013	Lexus	ES300h, ES350, LS460L, LS600hL	Yes	Yes
2013	Lexus	GS450h, LS460	No	Yes
2012-2013	Mercedes-Benz	CL-Class, CLS-Class, E-Class, E-Class Cabriolet, ML-Class, S-Class	Yes	Yes
2013	Mercedes-Benz	C-Class, GL-Class, GLK-Class, S-Class Hybrid, SLK-Class	Yes	Yes
2013	Mercedes-Benz	E-Class Hybrid, E-Class Wagon, SL-Class	Yes	No
2013	Subaru	Legacy, Outback	Yes	Yes
2011-2013	Volvo	S60, XC60	Yes	Yes
2011-2012	Volvo	S80, XC70	Yes	Yes

Table Note	*Note*
1	*All have FCW Except: 2011-2012 X5 xDrive35i/xDrive35d/xDrive50i and 2011-2013 X6 xDrive35i/xDrive50i*
2	*All have FCW Except: 2011 Active Hybrid 750i/750Li*
3	*2013 Ford Explorer has both FCW and LDW*
4	*2013 Honda FCX has LDW as standard equipment*

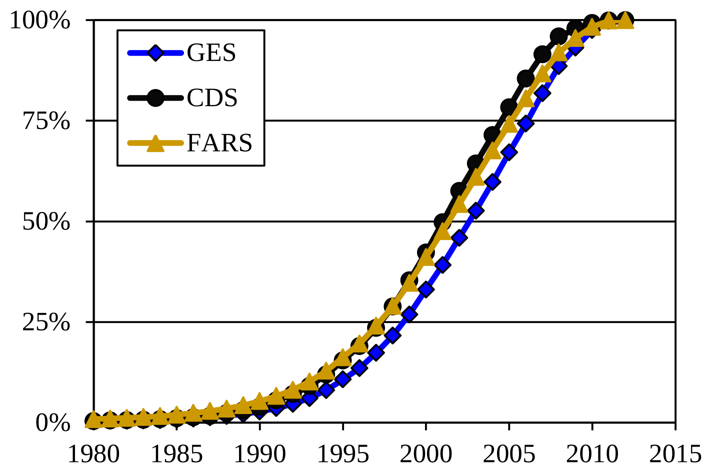


Figure 11. Cumulative Distribution of Model Year of Passenger Vehicles from GES 2010-2011, CDS 2007-2011, and FARS 2010-2011.

Using the list of vehicles that have FCW or LDW as optional equipment, we identified vehicles in GES, CDS, and FARS, shown in Table 7. GES had the largest proportion of vehicles which may have been equipped with either FCW or LDW. Only general model information is provided from the databases, so it is not possible to determine what optional equipment was installed on the vehicle. Even fewer vehicles that could possibly be equipped with FCW or LDW were involved in crashes where they would have potentially mitigated the effects of the collision. Only 16 cases from GES, 2 from CDS, and none from FARS had FCW as optional equipment and were involved in an applicable crash scenario. Only 5 cases from GES, none from CDS, and 5 from FARS had LDW as optional equipment and were involved in an applicable crash.

Table 7. Proportion of Vehicles with FCW or LDW as Optional Equipment in all Passenger Vehicles in GES 2010-2011, CDS 2007-2011, and FARS 2010-2011

	GES			CDS			FARS	
Category	**n**	**Freq.**	**%**	**n**	**Freq.**	**%**	**n**	**%**
Has FCW	134	14,689	0.08%	11	1,902	0.01%	39	0.05%
Has LDW	66	7,571	0.04%	2	62	0.00%	20	0.03%
Has Either	151	17,196	0.10%	11	1,902	0.01%	47	0.06%
All Other	160,594	17,927,349	99.90%	43,158	17,894,136	99.99%	78,837	99.94%
Total	160,745	17,944,546	100%	43,169	17,896,039	100%	78,884	100%

It is unlikely that many of the vehicles involved in applicable crash types were equipped with active safety systems. Even if the vehicle was of a make and model that could have FCW or LDW does not guarantee the system was equipped or operational on the vehicle. The databases only contain general make information and do not provide what optional equipment was installed on the vehicle. Some vehicles with optional packages can be identified by the vehicle's VIN, but this information is not available for all automakers. Due to the extremely small number of cases that could possibly have active safety systems, we have included all vehicles in the following analyses. Many of the vehicles that have FCW and LDW as optional equipment are model year 2013 vehicles, which did not appear in these datasets. Analysis of future years of these databases may require more scrutiny of which vehicles may or may not have active safety systems.

2.4.3. Crash Scenarios

The number of seriously injured occupants (MAIS3+) and fatalities vs. the total number of occupants for the most frequent crash scenarios is shown in Figure 12 and Figure 13. Points that fall above the diagonal line are overrepresented in injury or fatality frequency with respect to their exposure and *vice versa* for those points that fall below the diagonal line. Opposite direction, single vehicle control loss, and single vehicle crashes were the most overrepresented crash scenarios. Straight crossing path (SCP) and turning into/across path crashes were slightly overrepresented in injured drivers and fatalities. Rear-end collisions were the single most frequent crash mode (35% of occupants) but accounted for only 7.2% of MAIS33+ occupants and 6.8% of fatalities.

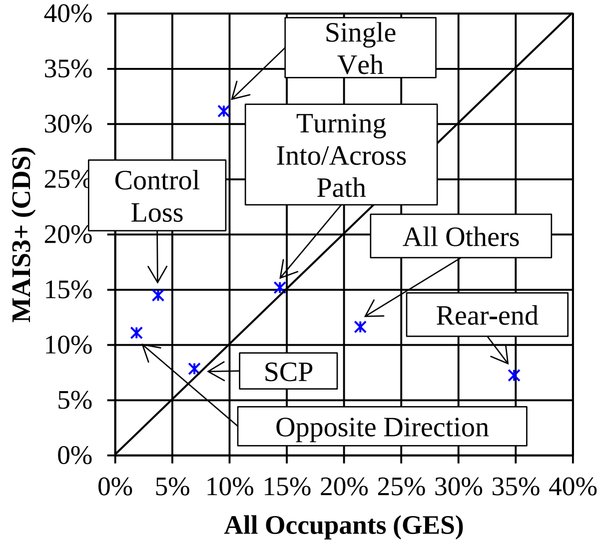


Figure 12. Number of Seriously Injured Occupants (MAIS3+) vs. Number of Occupants by Crash Scenario for Crashes involving at least one Passenger Vehicle.

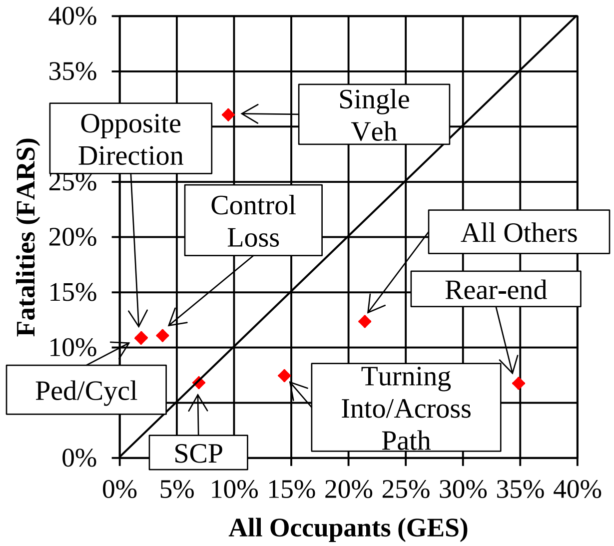


Figure 13. Number of Fatalities vs. Number of Occupants by Crash Scenario for Crashes involving at least one Passenger Vehicle.

Figure 14 shows the number of crashes from each data source for the most frequent pre-crash scenarios. CDS, GES, and NMVCCS have similar distribution of crashes. CDS and NMVCCS do not include pedestrian/cyclist crashes. It appears NMVCCS had slightly less rear-end collisions and slightly more turning collisions than GES and CDS. The number of crashes and occupants for all pre-crash scenarios are tabulated in the appendix.

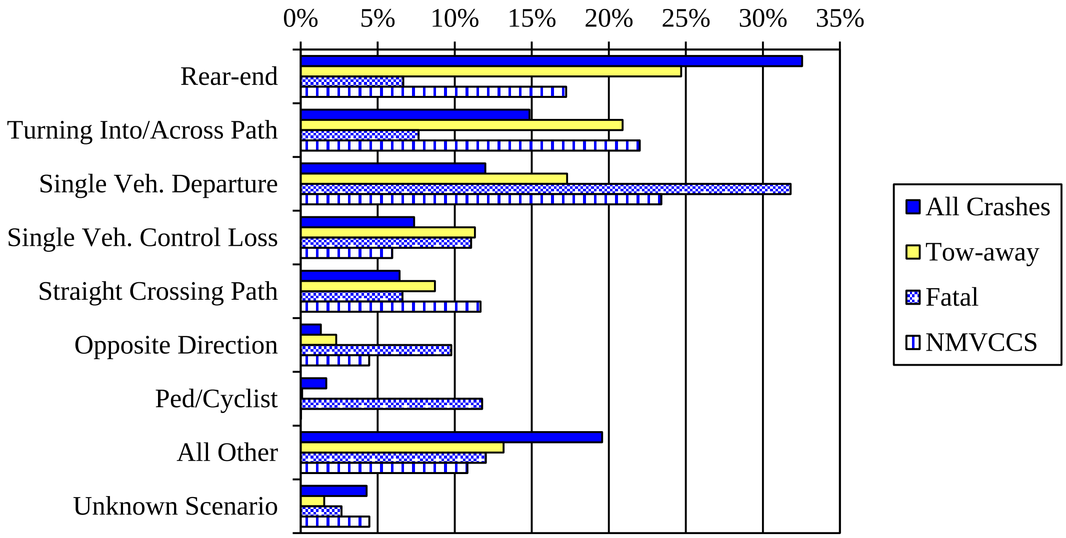


Figure 14. Proportion of All Crashes (GES), Tow-away Crashes (CDS), Fatal Crashes (FARS), and NMVCCS Crashes by Pre-Crash Scenario.

2.4.4. Active Safety Applicable Crash Scenarios

Figure 15 summarizes the number of occupants, seriously injured occupants, and fatalities applicable to FCW, LDW, and V2V/V2I systems using their pre-crash scenario only. FCW is applicable to the most number of exposed occupants, but is applicable to a smaller proportion of injured occupants and fatalities compared to LDW and V2V/V2I. In total, these three systems have the potential to mitigate 60% of seriously injured occupants and 65% of fatalities. Annually the three systems could potentially mitigate 3,258,217 crashes, 41,738 seriously injury crashes, and 18,367 fatal crashes.

2.4.5. Crash Causation in Active Safety Applicable Crashes

From NMVCCS, the critical reasons that lead to the crash occurring are shown in Figure 16 for crashes applicable to each system. Distraction was the most frequent critical reason in applicable crashes for all three systems. Over half of FCW and V2V/V2I applicable crashes had distraction as the critical reason. LDW applicable crashes had more performance and non-performance causes compared to FCW and V2V/V2I crashes.

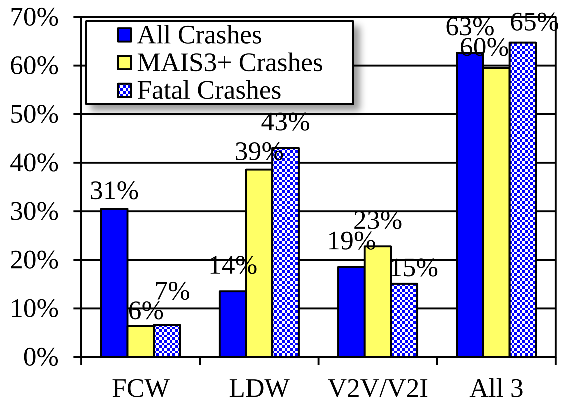


Figure 15. Proportions of All Severity, Serious Injury (MAIS3+), and Fatal Crashes with Applicable Pre-Crash Scenarios to Active Safety Systems.

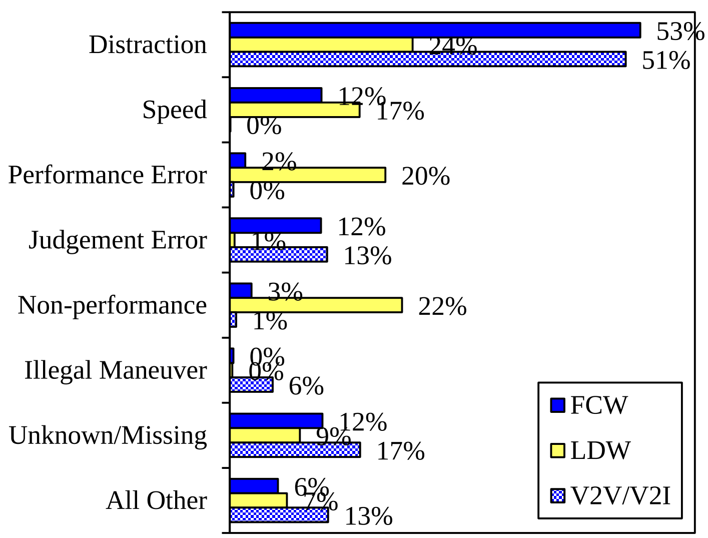


Figure 16. Distribution of Critical Events for Active Safety Applicable Crash Scenarios from NMVCCS.

Figure 17 shows the distribution of distraction critical reasons. In V2V/V2I applicable crashes, the most common distraction was inadequate surveillance, i.e. “looked but did not see.” Internal distraction, however, was the most common single categories for FCW and LDW applicable crashes.

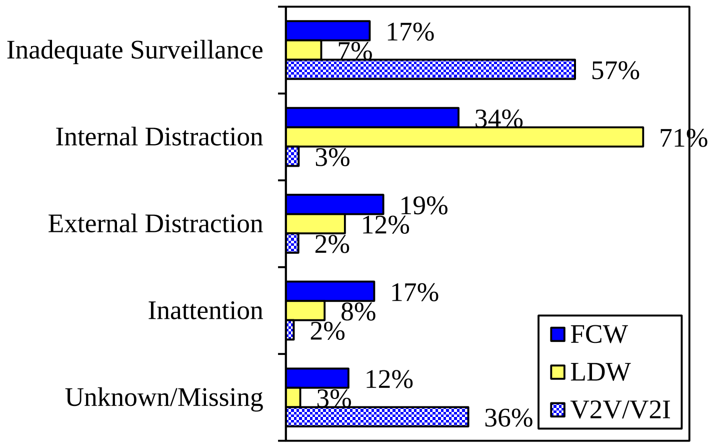


Figure 17. Distraction Critical Reason for Active Safety Applicable Crash Scenarios from NMVCCS.

Looking further at crashes with internal distraction as the critical reason, Figure 18 shows the distribution of causes of internal distractions. Text messaging was approximately one quarter of internal distractions for FCW and LDW applicable crashes, followed by reaching for objects and looking at other occupants for these two categories. V2V/V2I had only 3% of distraction crashes with internal distraction and thus is not shown in Figure 18.

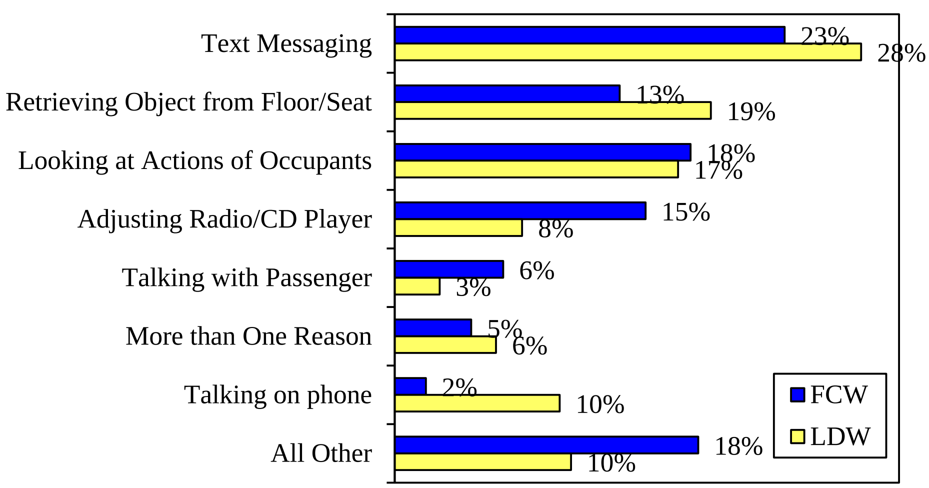


Figure 18. Distribution of Internal Distractions for Active Safety Applicable Crashes.

The 100-Car Naturalistic Driving Study performed by the Virginia Tech Transportation Research Institute was a seminal study. Just over 100 vehicles were instrumented and data was collected for one year of normal driving per vehicle. From this thousands of hours of driving data, the same type of contributing factors to crashes that is found in NMVCCS can be derived. Two studies examined 100-car data with respect to rear-end crashes and run off road crashes. McLaughlin *et al.* analyzed 122 road departure crashes and near-crashes from the 100-Car Naturalistic Driving Study [41]. Lee *et al.* analyzed 385 rear-end crashes and near-crashes [70]. The following meta-analysis uses data shown in Figure 2 of McLaughlin *et al.* and Table 9 or Lee *et al.*

Table 8 compares the 100-Car results with the current NMVCCS study. McLaughlin found that 36% of their departure events occurred due to distraction. Our NMVCCS study found that approximately 24% of crashes were caused by distraction. The largest difference was that the 100-car data had far less cell phone dialing or text messaging (8%) compared to the NMVCCS data (22%). The distraction from the 100-car data was determined from driver video recorded as part of the study. The investigators could not determine if the cell phone use was dialing/hanging up or text messaging so these two categories were combined. For the rear-end study, Lee found that 44% of rear-end crashes and near-crashes were caused by distraction compared to 53% of NMVCCS rear-ends. The 100-car analysis separated external distraction from "driving related inattention to forward roadway," which were combined in Table 8. External distraction accounted for 5% of while driving related inattention was 29% of events. The largest subcategory within the driving inattention category was looking out the left window, accounting for 23% of crashes and 11% of near-crashes. In NMVCCS, these external distractions, although driving related, would have been categorized as external distraction events. Other differences between the 100-car and NMVCCS rear-end crashes was a small proportion of drivers in NMVCCS talking on the phone and larger proportion of drivers in NMVCCS daydreaming, or being inattentive.

Table 8. Comparison of 100-Car Naturalistic Driving Studies (McLaughlin *et al.* [41] and Lee et al. [70]) and NMVCCS Study.

Category		100-Car Study (Rear-end)[1,2]	NMVCCS FCW	100-Car Study (Departures)[1]	NMVCCS LDW
Distraction Crashes		44%	53%	36%	24%
	External Distraction	35%	19%	22%	12%
	Inattention (Daydreaming)	6%	17%	0%	8%
	OEM Device	4%	7%	12%	6%
	Talking to Passenger	3%	2%	12%	2%
	Talking on Cell	12%	1%	12%	7%
	Reading	2%	0%	8%	1%
	Cell Dialing + Texting	9%	9%	8%	22%
	Eat/Drink/Smoke	6%	3%	6%	3%
	Glance at Passenger	8%	6%	2%	12%
	Reaching	5%	5%	6%	13%
	All Other	12%	31%	12%	15%
	Total	100%	100%	100%	100%

[1]Combined External Secondary Tasks and Traffic Related External Glances for 100-Car Data
[2]Combined "Crash" and "Near-Crash" Events into one category, n = 173 distraction-related events

Lee *et al.* compared their distraction causes to a study that used NASS/CDS as the data source for distraction (see Table 10 in Lee *et al.*) [70]. As noted earlier, GES, CDS, and FARS have limited detailed information on crash causation. Because crashes from the traditional databases are investigated days or weeks after the crash occur or from police accident reports only, they are less likely to accurately contain distraction related information. A recent study by the National Safety Council reviewed 180 crashes from FARS using media reports of the crashes and by some independent contact with witnesses [71]. They found that 50% of FARS crashes that had a driver that admitted to using a cell phone prior to the crash was not coded as having distraction in FARS. The results shown in Table 8 of the current study shows that NMVCCS appears to be valid source of distraction information in crashes that could be mitigated by FCW or LDW.

Using the prevalence of distraction critical reasons found from NMVCCS, we can adjust the target population estimates in Figure 15 using the pre-crash scenarios only. The target population adjusted for driver distraction for FCW, LDW, and V2V/V2I systems is shown in Figure 19. In total, these three systems could mitigate approximately 1 in 5 all severity, serious injury, and fatal crashes that occur in the

U.S. Table 9 summarizes the estimated annual number of all severity, serious injury, and fatal crashes applicable to the three active safety systems, adjusted for driver distraction.

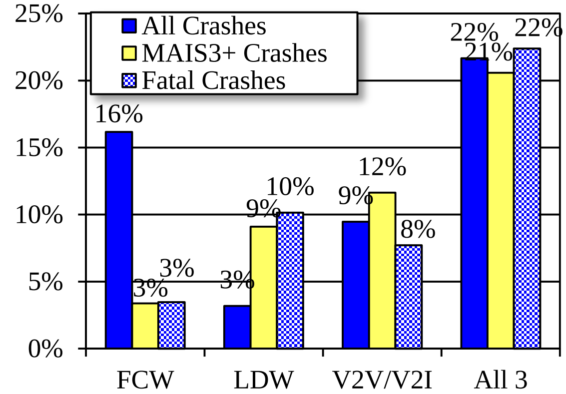


Figure 19. Proportions of All Severity, Serious Injury (MAIS3+), and Fatal Crashes Adjusted for Distraction Related to Active Safety Systems.

Table 9. Annual Number of Crashes, Serious Injury, and Fatal Crashes Applicable to Active Safety Systems, Adjusted for Driver Distraction

Group	FCW	LDW	V2V/V2I	All 3
All Crashes	841,094	166,061	492,869	1,126,865
MAIS3+ Crashes	2,080	5,605	7,168	14,435
Fatal Crashes	986	2,880	2,190	6,352

2.5. DISCUSSION

An accurate estimate of the target population for a safety system is the critical first step in predicting its potential benefits in the vehicle fleet. The pre-crash scenario, i.e. the physical configuration of the vehicles, is important because it defines which crashes the sensors and algorithms of a proposed active safety system have the most likelihood of activating successfully. Often ignored in target populations, however, are the driver behaviors that the systems will be most likely to mitigate. For current active safety systems, FCW, LDW, and V2V/V2I systems, the crash cause that they will be most likely to mitigate is distraction. Because all three systems, at least in near-term applications, rely heavily on warning the driver, they will likely not mitigate crashes primarily caused by excessive speed, close following distance, or vehicle failure.

We showed in this study that NMVCCS is a valid data source for crash causation by comparing the distraction critical events to those identified in the 100-car naturalistic driving study. Although not presented in this study, the traditional databases of GES, CDS, and FARS do not contain accurate estimates of distraction critical reasons [70].

This study has several limitations. We relied on coded variables in each database to perform our analysis. We were not able to examine all cases on a case-by-case basis. In developing the scenarios, however, we utilized cases from NASS/CDS for validation. CDS cases have written narratives, scene diagrams, and scene photographs that are invaluable to for assessing the validity of the coded variables. We are confident that our pre-crash scenario coding scheme classifies similar collisions into groups. Target populations are upper bounds estimates of the number of crashes that could be potentially mitigated or prevented by a system. They do not take into account the specific driver and system performance of each crash that may lead the systems to be less effective than intended. One major improvement over past target population estimates that this study introduced was by accounting for driver distraction in our target population estimates. FCW and V2V/V2I applicable scenarios had approximately 50% of crashes caused by distraction, while LDW only had 24%. Thus, the estimated target population for LDW was 10% of fatal crashes, down from 43% of all fatal crashes by pre-crash scenario only.

These crash scenarios are unique compared to past efforts in that they are comparable between the three major NHTSA databases, GES, CDS, and FARS. This comparison is only possible for GES and FARS 2010 and later due to major changes in pre-crash variables that resulted from harmonization of pre-crash variables among these databases. Common practice is to use the last 5 to 10 years of data when estimating target populations from these data to reduce the variability. As future years of GES and FARS become available, this analysis can be repeated with more years of data.

2.6. CONCLUSIONS

This paper presented novel crash scenarios that describe the pre-crash configuration in crashes from real-world crash databases. These scenarios can be applied to these databases to identify the target populations for active safety systems. We identified the target population for three emerging active safety systems: FCW, LDW, and V2V/V2I systems. FCW was applicable to the largest number of exposed occupants, but was not applicable to as many seriously injured occupants and fatalities as compared to LDW and V2V/V2I. In total, the pre-crash scenarios that these three systems could potentially mitigate were 60% of seriously injured occupants and 65% of fatal crashes, representing 3.3 million crashes and 18,367 fatal crashes annually. Using the NMVCCS database, we estimated the cause of these crashes with applicable pre-crash scenarios. We found that 53% FCW, 24% of LDW, and 51% of V2V/V2I applicable scenarios were caused by driver distraction. Adjusting for distraction, these active safety systems could potentially mitigate approximately 1 in 5 crashes in the U.S., including serious injury and fatal crashes. Annually, this is 1.1 million all severity, 14,000 serious injury (MAIS3+), and 6,352 fatal crashes.

3. Development and Evaluation of Driver Reaction Models to Active Safety Systems

3.1. INTRODUCTION

The driver response to activation of an active safety system is critical to model system benefits. The driver control actions are described by the brake, accelerator, and/or steering input to the vehicle. The objective of this chapter is to develop a general model for driver reaction to an active safety system and identify the data sources that can be used to develop and verify such models. The chapter will also introduce a novel method for using Event Data Recorders to verify brake initiation timing and magnitude.

3.2. METHODOLOGY

3.2.1. General Model for Driver Reaction

The main crash avoidance maneuvers of a driver are steering, braking, or a combination of the two. The incidence of these maneuvers is highly dependent on the crash type. For example, in rear-end collisions steering avoidance maneuvers are very rare accounting for less than 5% of crashes [72]. Naturalistic data from the 100-car study showed that braking alone was the avoidance maneuver in 86% of events compared to steering only in only 1.8% of events and braking and steering in 27% of events [70]. These naturalistic events included 7 crashes and 380 near-crashes, where emergency maneuvers outside of normal driving were required. In contrast, avoidance of a roadside fixed object may be dominated by steering response. To model the driver response to an active safety system, the driver response must be hypothesized based on observations of the crash population.

After a generic response is identified for the target crash mode, a parametric description of the response can be developed and the parameters of this response derived from experimentation. Figure 20 shows a generic response that could be used for either braking or steering response to a warning or event. The driver input has some initial value, Ω_0, that is assumed constant prior to an event occurring, e.g. a warning. After the event occurs, there is a driver reaction time (*RT*) followed by a driver response with a magnitude of Ω and rate j.

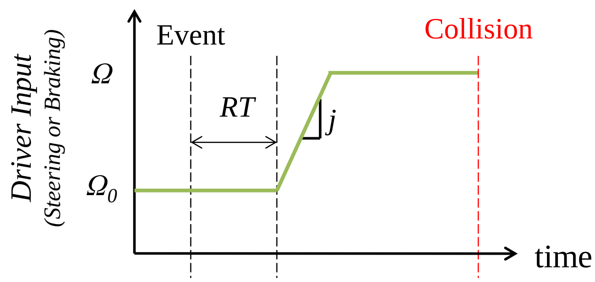


Figure 20. Simple Driver Input Model for Either Braking or Steering.

3.2.2.   Data Sources for Model Parameters

The data sources to derive these pre-crash parameters can come from a diverse pool of study methodologies. Real-world crash data is useful for identifying overall trends in the population, e.g. braking vs. steering response. Crash databases lack detail to derive specific response parameters, however. Experiments, primarily performed on a test track or a driving simulator, are the primary data sources available for deriving these values. The advantage of test track and simulator studies is the experimental control offered by these methodologies. Driving simulators have become a powerful tool that many argue is a valid method for obtaining driver response data [73, 74]. In a simulator, the scenario can be closely controlled and driver response accurately measured. The disadvantage of both test track and simulator studies is the concern the scenarios in the experiments may not be representative of real-world driving.

Real-world data, such as naturalistic driving studies or event data recorders, offers the benefit of measuring driver responses in real world driving. The small number of cases per scenario and other uncertainties are limitations of this real-world data. The availability of naturalistic data is still growing with many naturalistic driving studies being performed or recently completed, such as the SHRP-2 and IVBSS studies [75, 76]. These new data sources, that are just now starting to be analyzed, may be future sources of driver response data.

Currently, however, the most feasible source these driver response data is from the driving simulator and test track literature. In our approach, we will use crash database data to verify the validity of this experimental data. In the next section, we will present a novel method for verifying driver brake timing studies using real-world event data recorder data.

3.2.3. Verification of Braking Parameters using Event Data Recorder Data

One promising method to study driver pre-crash behavior in real-world crashes is with data retrieved post-crash from the Event Data Recorders (EDR) installed in most passenger vehicles. EDRs are the black box recorder devices that are installed on most new passenger vehicles. EDRs are usually associated with the airbag control module of the vehicle and are able to store vehicle information after a crash occurs. NASS/CDS investigators download the EDR data from involved vehicle using the Bosch Crash Data Retrieval (CDR) tool. This publically available tool allows investigators to download the EDR records to a computer via the vehicle diagnostic port or by directly interfacing with the airbag control module. NASS/CDS investigators have been using the Bosch tool to download General Motors (GM) EDRs since case year 2000, Ford since year 2002, and Chrysler since year 2008. In total, 6,131 EDRs from these three makes have been downloaded from NASS/CDS years 2000 to 2011, the most recent year of data available.

Some EDRs can record vehicle data prior to the crash, namely vehicle speed, brake application, and throttle position. Figure 21 shows the scene diagram and vehicle damage from a rear-end crash involving a 2002 Chevrolet S-10 pickup truck. The truck impacted the rear of a vehicle stopped in traffic. The driver of the striking vehicle, a 43-year-old male, was not injured in the crash. The driver of the struck vehicle, a 2002 Chevrolet Trailblazer, was transported to a trauma center. This 23-year-old female suffered only minor neck injuries causing a reported 3 lost working days.

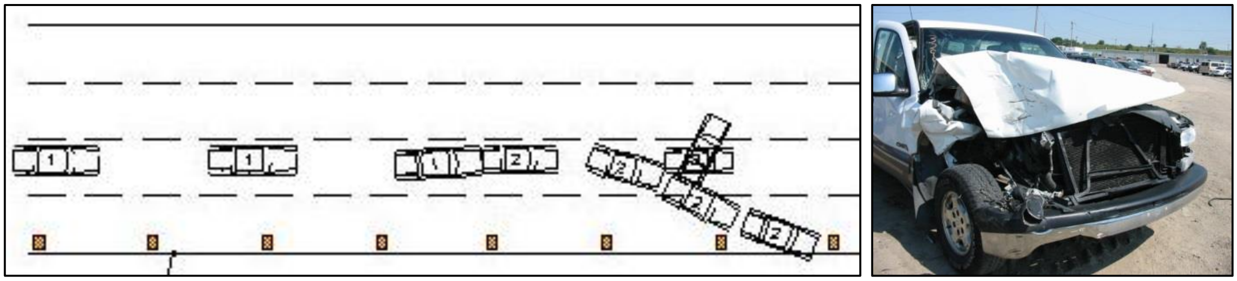


Figure 21. Scene Diagram and Vehicle Damage for Rear-end Crash Involving a 2002 Chevrolet S-10 Pickup into a Stopped Vehicle (NASS/CDS Case 2006-74-098).

Figure 22 shows the pre-crash data from the EDR from the Chevrolet S-10 pickup. On approach, the vehicle was traveling at approximately 88.5 kph (55 mph). Two seconds prior to the impact, the driver applied the brakes, slowing the vehicle.

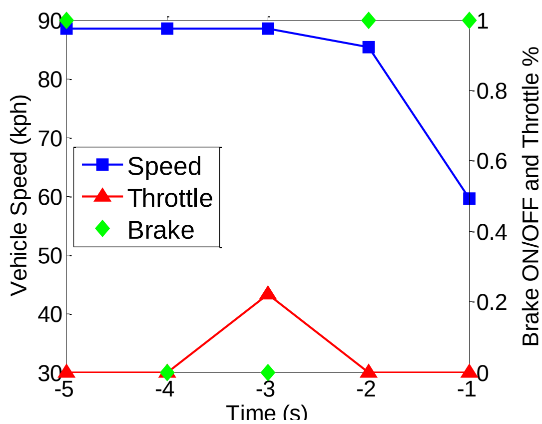


Figure 22. Pre-Crash EDR Data Recovered from the Striking Vehicle in NASS/CDS 2006-74-098.

Like the example shown in Figure 22, most EDRs store pre-crash data 5 seconds prior to the crash with a sample rate of 1 sample per second. Newer GM and Ford modules capture data at 2 samples per second for 5 seconds. Recent Chrysler modules store 5 seconds of data collected at 10 samples per second. Following recently passed regulations in the U.S., all new EDRs will record this pre-crash data for 5 seconds, at a minimum of 2 samples per second [77]. EDR pre-crash data has been used in the past to investigate driver pre-crash maneuvers [78-80] as well as studying crash and injury severity [81-91].

3.2.4. Computing Average Deceleration and Time to Collision of Brake Activation from EDR Data

The pre-crash vehicle speeds recorded by the EDR can be used to determine the average deceleration of vehicles involved in rear-end crashes [78]. Figure 23 shows the process for determining average deceleration from the vehicle speed recorded by the EDR. The average acceleration is the change in velocity between the start of braking (v_1) and the last EDR recorded record (v_2) over the time span Δt. The start of braking was determined from visual inspection of the vehicle speed and brake ON/OFF time histories. For example, examining the pre-crash vehicle speed and brake histories in Figure 22, braking initiated approximately 2 seconds prior to the crash. The vehicle slowed from 85.3 kph (53 mph) to 59.5 kph (37 mph) over 1 second, corresponding to an average deceleration of 0.73 g.

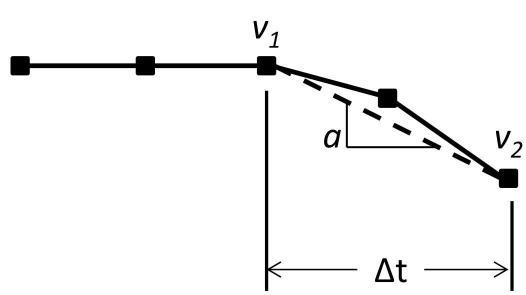


Figure 23. Computation of Average Brake Deceleration using EDR Pre-crash Speed.

One common metric for system activation in FCAS is Time To Collision (TTC), the instantaneous range over range rate of a vehicle approaching another object [93]. TTC is computed as shown in Figure 24 and has units of seconds.

$$TTC = \frac{x_0}{V_{12}}$$

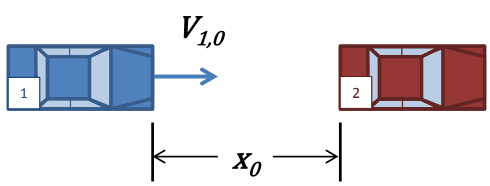


Figure 24. Calculation of Time To Collision (TTC) in Rear-end Crashes.

Assuming the struck vehicle, vehicle 2 in Figure 24, is stationary prior to the crash, kinematic equations for the striking vehicle can be solved for the TTC at braking initiation, TTC_{brake},

$$\mathrm{TTC_{brake}} = t_s - \frac{1}{2V_{1,0}} a t_s^2 \tag{1}$$

where t_s is the time prior to the collision brake was initiated, $V_{1,0}$ is vehicle one's speed at brake initiation, and a is the average deceleration during braking. In our sample of real-world collisions very few collisions had EDR data recovered from both the striking and the struck vehicle. As a result, the acceleration and speed of the struck vehicle was unknown. Therefore, TTC was estimated using equation (1) in crashes where the investigator indicated the struck vehicle was stopped prior to the crash. Some cases had braking indicated on the last recorded pre-crash record prior to the crash and thus an average deceleration could not be computed. For these cases, the mean average deceleration for the rest of the EDRs was used when computing TTC.

3.2.5. Uncertainty in Pre-crash Reported Time

Most EDRs store pre-crash data in a circular buffer, replacing the oldest data points with newer ones at regularly spaced intervals. When a crash event occurs, the data in the buffer is stored in the EDR memory and reported as -5, -4, -3, -2, -1 seconds prior to the crash, for example. The actual time until the collision occurred is at least its reported value in the pre-crash record and could be closer to the collision by as much as 1 time step, as shown in Figure 25. The time shift of the EDR pre-crash record is unknown in real-world crashes.

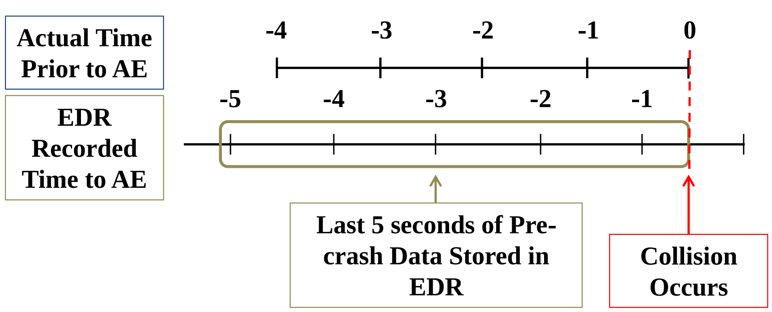


Figure 25. Schematic Example of Time Uncertainty in EDR Pre-Crash Records.

The time offset of the reported pre-crash time and the actual time can be assumed to be uniformly distributed between 0 and one time step. Therefore, the expected value of the time offset is half of the pre-crash data time step of the module. To account for this time uncertainty in TTC calculations, we will present three values that represent the feasible range of time uncertainty, an example of which is shown in Figure 26. The lower bonds on the time estimate is the time history as recorded. The nominal time value is equal to adding half a pre-crash data time step to the reported time. Finally, the upper bound is found by adding a full time step to the reported time.

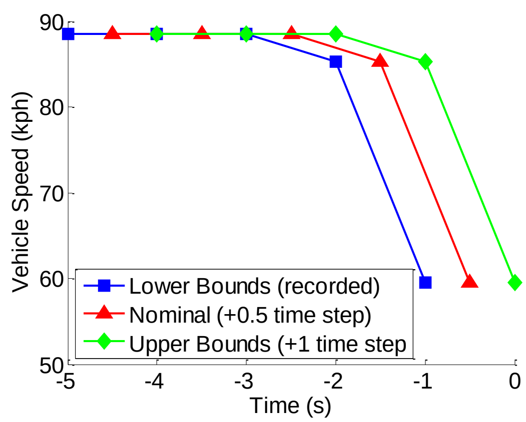


Figure 26. Example of Time Shift for EDR Data to Account for Time Uncertainty

3.3. RESULTS

3.3.1. Generic Model of FCAS

As important as the driver reaction of the driver to the system is the response of the active safety system. Therefore, in order to fully define a driver reaction model, a model of a generic FCAS must be defined. A simple metric that some FCAS use to judge collision threat is TTC, described above. TTC has been shown to directly relate to driver's threat recognition in frontal collisions and is readily measured by radar sensors [80]. A FCAS that has the three components will be used in this study: FCW, Dynamic Brake Support (DBS), and Crash Imminent Braking (CIB). Although most production FCAS systems in the U.S. only have FCW, DBS and CIB are available in some production vehicles and are expected to be features of future FCAS. The activation times of such a system is described in Aoki *et al.* [93]. Figure 27 shows the activation times and system components of this system, which will be used as the basis for the FCAS components in this study. DBS will double the driver braking effort and CIB will add 0.6 g of deceleration to the vehicle braking level.

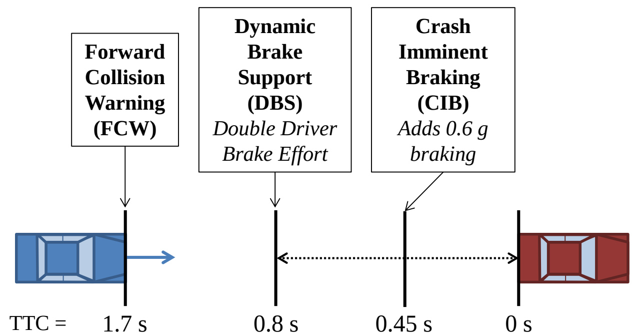


Figure 27. Activation Timing of FCAS Components Leading to a Crash [93].

3.3.2. Braking Reaction Model for FCAS

This section will define how the driver reaction model interacts with the FCAS system defined above. For rear-end crashes, braking is the primary collision avoidance response. Reaction time is important for FCAS algorithms because it determines what system(s) will activate. For example, consider four scenarios of drivers applying the brakes in response to a warning, shown in Figure 28. FCW warns the driver 1.7 s before the collision. A fast reaction time (scenario 1) will cause the driver to apply the brakes before the threshold for DBS resulting in only driver braking effort. However, a medium reaction time (scenario 2) will cause DBS to activate once the driver starts braking, doubling the driver braking effort. A slow reaction time (scenario 3) will still cause DBS to activate, but braking time will be shorter. Finally, if the reaction time is greater than 1.7 s, the crash will occur before the driver applies the brake (scenario 4) and only CIB will activate.

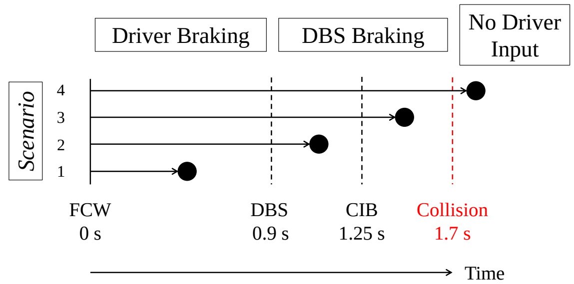


Figure 28. Schematic of FCAS component activation based on reaction time for fast (1), normal (2), slow (3), and no response (4). Filled circles indicate the time of driver brake application.

A distribution of driver brake reaction times was used as developed by Sivak *et al.* [96]. The Sivak study collected reaction times to visual warnings of 1,644 drivers and found a mean reaction time of 1.21 s with a standard deviation of 0.63 s. This study was performed on public roads in 1982 and involved measuring the time between brake lights being presented to a uninformed, following driver and their braking response. Assuming a lognormal distribution of reaction times, this distribution has been used to investigate FCAS warning response in previous studies [97]. This distribution was used because of its large sample size and use by past researchers to describe brake reaction time. Other studies with smaller populations and scopes were also considered and most were within the brake reaction times found by Sivak *et al.* [97-99].

Figure 29 shows the probability density function of driver response times. For all drivers in the population, 17% would have a reaction time greater than 1.7 s, thus having no response prior to the collision. Characteristic “fast”, “medium”, and “slow” response times were found from the remaining 83% of drivers. Characteristic “slow” and “fast” responses corresponded to 20% of the population. The median response time, 1.07 s, was used as the “medium” response time, which was used to characterize the remaining 43% of the population.

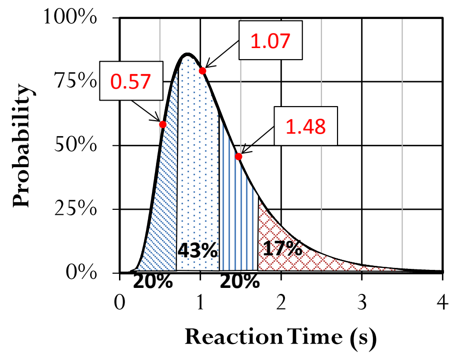


Figure 29. Probability density function of driver reaction times and characteristic reaction times used for FCAS simulations.

The maneuvers of the driver prior to the collision without FCAS affect the vehicle speeds when FCAS components activate. These before-FCAS maneuvers will be considered in the crash severity reduction model presented in Chapter 5. Drivers from striking vehicles were put into three groups based on their coded pre-crash maneuvers from NASS/CDS: 1) not braking, 2) braking, or 3) accelerating. The "not braking" group was assumed to not apply the brakes at all prior to the collision. The "braking" group could apply the brakes in two ways: late and hard braking, as a driver who was inattentive and realized a collision risk too late to avoid the collision, or early and weak braking, as a driver who applies the brakes to avoid a collision but misjudges the brake magnitude necessary to avoid the collision. The "braking" group was simulated with both late, hard braking and early, weak braking. In the late, hard braking scenario, the driver was assumed to apply the brakes at a time to collision of 0.4 s, too late to avoid all collision in the dataset. The accelerating group was assumed to apply a constant acceleration.

Driver braking magnitude was assumed to be a constant level. Hard braking for the striking vehicle produced a 0.4 g vehicle deceleration, while weak braking created 0.2 g of deceleration. These values were found from a combination of driving simulator experiments and examination of EDR data [93]. The maximum vehicle deceleration possible was limited to 0.8 g. Simulations with FCAS assumed the driver of the striking vehicle would apply the brakes at the hard level (0.4 g) in response to the FCW.

Three algorithms were simulated: 1) FCW only, 2) FCW + DBS, and 3) FCW + DBS + CIB. The combination of the four before-FCAS maneuvers and four response times created 16 possible braking pulses after FCAS implementation for each algorithm. A schematic of the 16 possible braking pulses by pre-crash maneuver and response time is shown for the FCW + DBS + CIB system in Figure 30. The columns of the figure are the before-FCAS maneuvers of the driver while the rows are the driver response to FCAS. The dashed line shows the driver braking before FCAS and the solid line shows the vehicle braking with FCAS in response to the driver braking input with FCAS. Depending on the coded before-FCAS maneuvers, one, two or three of these columns will be simulated, as described later in this section. A similar schematic is shown for the FCW + DBS and FCW only algorithms in Figure 31. The solid lines show the FCW + DBS algorithm and the small dashed lines show the braking pulse for the FCW only algorithm. For the "no response" category, neither algorithm has any benefit. For the "fast response" category, braking initiates before the threshold for DBS activation, so the two algorithms cause the same braking pulse. Because there is no CIB activation, braking starts later for "slow" response category compared to the FCW + DBS + CIB algorithm.

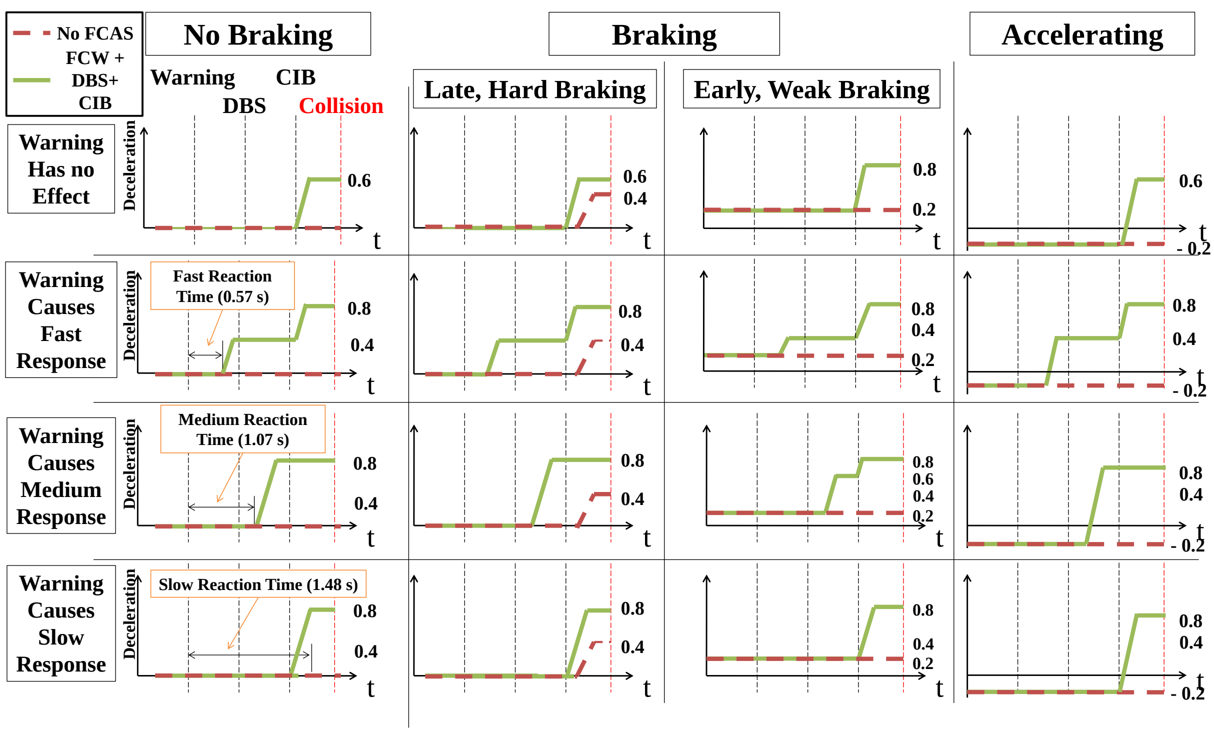


Figure 30. Schematic Representation of FCAS Braking Pulses for Pre-crash Maneuver and Response Time for a FCW + DBS + CIB Algorithm.

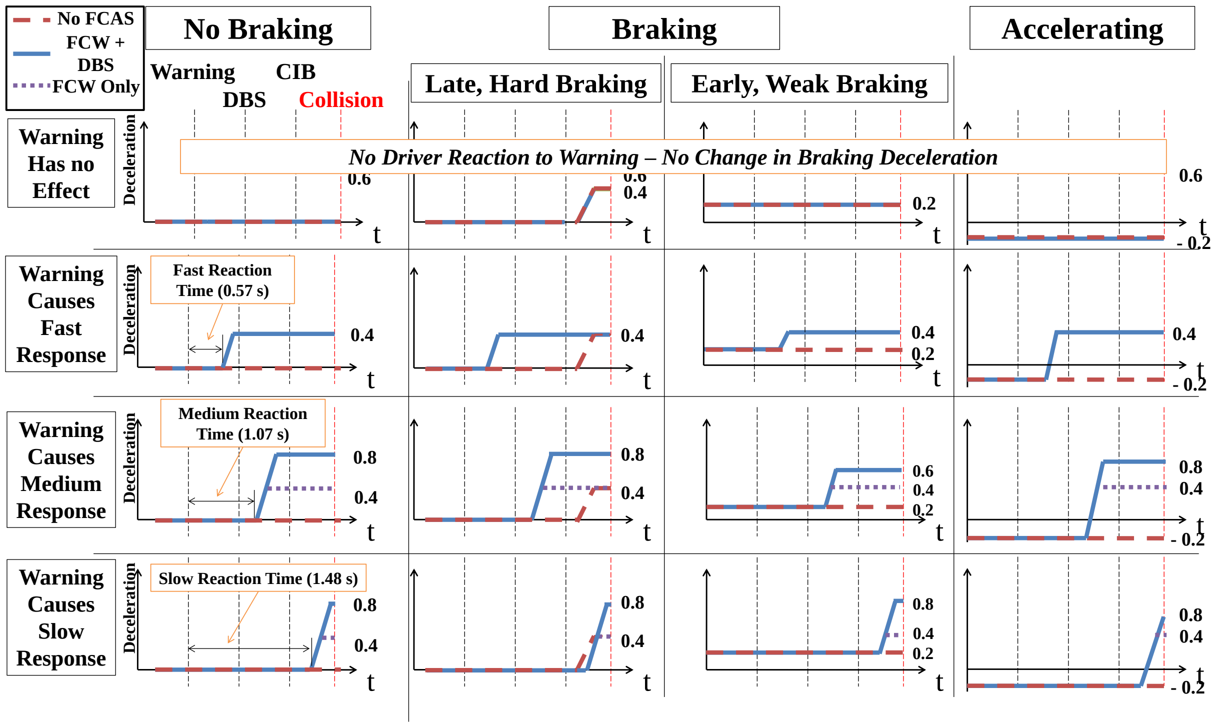


Figure 31. Schematic Representation of FCAS Braking Pulses for FCW + DBS and FCW only Algorithms.

To estimate overall algorithm effectiveness, each crash was simulated multiple times with different scenarios shown in Figure 30 and Figure 31. The number of simulations for each case was dependent on the NASS/CDS coded avoidance maneuver (braking, no braking, accelerating). Each simulation was assigned a simulation weight, w_j, based on probability of the response occurring in the general population. The computation of the number of crashes and number of injuries with the system are done using the simulation weights, as discussed in Chapter 1.

For cases where the driver was not braking or accelerating before FCAS (first column), the simulation weights were 0.17 for the no effect simulation, 0.20 for the fast response simulation, 0.43 to the medium response simulation, and 0.20 to the slow response simulation. These are the weights that represent the proportion of the population with each characteristic reaction time, as shown in Figure 29. For cases where the driver was accelerating before FCAS (column 4), the simulation weights were the same as for not braking before FCAS (column 1).

For cases that reported driver braking (columns 2 and 3), it was assumed that the late-hard scenario occurred in 80% of cases and early-weak braking scenarios occurred in 20% of cases. This distribution is based upon results from EDR data presented later in this chapter. The case weights for each simulation for those crashes with braking are shown in Table 10.

Table 10. Distribution of Simulation Weights for Cases with Braking Pre-Crash Maneuver prior to FCAS

			Maneuver[a]	
			HLB	WEB
			80%	20%
Response Time	No Response	17%	0.136	0.034
	Fast Response	20%	0.160	0.040
	Medium Response	43%	0.344	0.086
	Slow Response	20%	0.160	0.040

[a]HLB – hard, late braking, WEB – weak, early braking

A large number of cases (14.0%) had a missing or unknown pre-crash vehicle maneuver for the striking vehicle. This was coded in NASS/CDS when the investigator was unable to determine the pre-crash maneuver with confidence. For cases with unknown or missing pre-crash vehicle maneuver, simulations for braking and no braking before FCAS were performed (columns 1, 2, and 3). Simulation weights for those cases with unknown pre-crash maneuver were found by multiplying the reaction time probabilities by the proportion of the pre-crash maneuver from the crash population, shown in Table 11. Of rear-end collisions with known braking status, 29% were not braking and 71% were braking, with almost none (<1%) accelerating.

Table 11. Distribution of Case Weight for Cases with Unknown Pre-Crash Maneuver prior to FCAS

				Maneuver[a]	
			NB	HLB	WEB
			29%	56.8%	14.2%
Response Time	No Response	17%	0.0493	0.09656	0.02414
	Fast Response	20%	0.0580	0.11360	0.02840
	Medium Response	43%	0.1247	0.24424	0.06106
	Slow Response	20%	0.0580	0.11360	0.02840

[a]NB – no braking, HLB – hard, late braking, WEB – weak, early braking.

3.3.3. Verification of Braking parameters using EDR Data

Table 12 lists the selected cases for this study. NASS/CDS years 2000 to 2011 contain 57,223 collisions with a weighted frequency of over 27.4 million crashes. Of these, 4.7 million or 17% of collisions were rear-end collisions where the lead vehicle was stopped or traveling slower at a constant speed. Rear-end collisions were selected using the pre-crash critical event and accident type variables reported in NASS/CDS, as discussed in Chapter 2. From these rear-end crashes, there were 168 cases where the striking vehicle had an EDR that contained pre-crash information recovered by the NASS/CDS investigators. The vehicle speed recorded on the EDR is sampled either from wheel speed or transmission speed sensors. Wheel lock-up or other traction loss can make vehicle speed estimates inaccurate. EDRs where there was greater than 1 g of deceleration between any two data points were discarded as in Aoki *et al.* [93].

Table 12. Number and Weighted Frequency of Selected Crashes

Group	n	Frequency
NASS/CDS 2000-2011	57,223	27,444,335
Rear-end Collisions	6,748	4,734,660
Rear-end with Locked Deployment Event	168	76,234
Valid Vehicle Speed Record	143	68,487

The braking avoidance maneuvers derived from the EDR pre-crash data are tabulated in Table 13. In 28% of rear-end crashes, the driver had little or no brake application.

Table 13. Braking Avoidance Maneuver from EDR Pre-crash Vehicle Speed and Brake Switch Status

Braking Avoidance	n	Frequency	%
Little or No Braking	47	19,391	28.3
Braking	96	49,096	71.7
Total	143	68,487	100

For the 96 cases with braking, 8 cases had braking indicated at the last pre-crash event record. For these 8 cases, the average braking deceleration could not be computed because there was no observable change in velocity on the pre-crash record. For the remaining 88 cases (weighted frequency of 41,976), the mean braking deceleration was -0.40 g and the median brake deceleration was -0.41 g.

Table 14 summarizes the number of crashes with any occupant that had a Maximum Abbreviated Injury Score (MAIS) of 2 or greater or was fatally injured (MAIS2+). The AIS is a scale that rates the threat to life of individual injuries. It is derived from medical records by trained AIS coding technicians. Examples of AIS2 injuries are multiple rib fractures to one side of the ribs, major lacerations, and loss of consciousness less than 1 hour. In the group of rear-end collisions, 5% of crashes resulted in an MAIS2+ injured occupant. In these injury crashes, only 35% of striking vehicle drivers applied brakes prior to the collision compared to 74% of drivers in the uninjured group. As a result, the mean of the last recorded pre-crash vehicle speed was lower for the uninjured group compared to the injured group. This result shows that drivers who do not brake are often involved in crashes that result in moderate to fatal injuries. These crashes where there is little or no braking prior to impact stand to benefit the most from active safety FCAS.

Table 14. Crashes with Injury (MAIS2+) and Brake Avoidance Maneuvers in Rear-end Crashes

	Crashes			Striking Vehicle Braking			Mean Last Recorded Speed
Group	**n**	**Freq.**	**%**	**n**	**Freq.**	**%**	**(kph)**
Injured (MAIS2+)	32	3,613	5.3%	16	1,269	35.1%	71.2
Uninjured	111	64,874	94.7%	80	47,827	73.7%	50.5
Total	143	68,487	100%	96	49,097	71.7%	51.6

Figure 32 shows the average brake deceleration as a function of brake initiation time with a linear regression line for the data. The 8 cases where braking started at the last recorded pre-crash time were excluded from the 96 cases that had driver braking, leaving 88 cases displayed in Figure 32. Although the data shows a trend of increased braking deceleration as brake initiation time is closer to the impact, the data has significant scatter. The R-squared value for the linear regression line is 0.095. Most of the modules have a time step of 1 second, as can be seen by the discretized columns of points at -1.5 and 2.5 seconds.

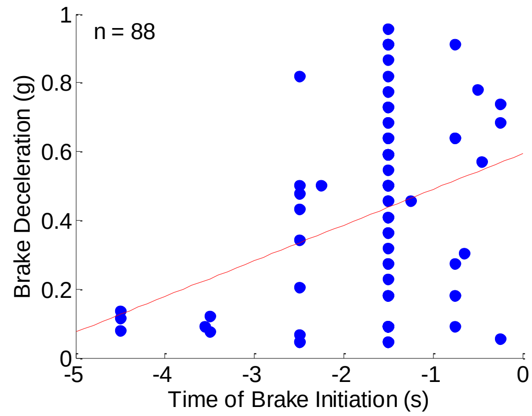


Figure 32. Average Brake Deceleration vs. Nominal Brake Initiation Time in Rear-end Collisions.

The average braking deceleration as a function of vehicle speed at the time of brake initiation is shown in Figure 33. Like Figure 32, there is considerable scatter in the data. There does not appear to be a correlation between speed and brake deceleration for this sample.

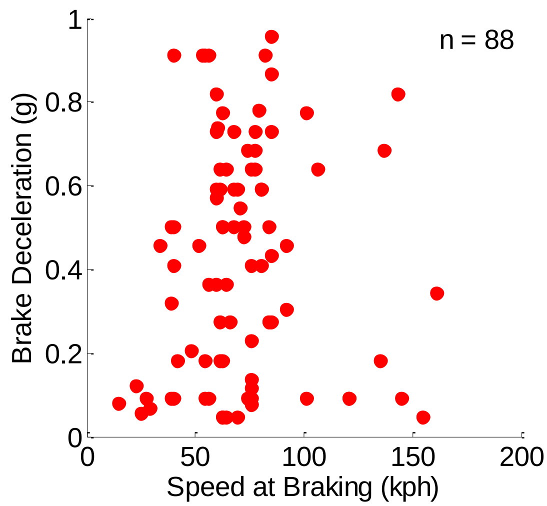


Figure 33. Average Brake Deceleration vs. Speed at Braking in Rear-end Collisions.

The EDR pre-crash record indicates approximately how many seconds prior to the collision braking started. The TTC at brake initiation, however, is a function of the initial relative velocities and acceleration of the striking vehicle. Because the acceleration and speed of the struck vehicle is often unknown, we computed TTC at brake initiation for rear-end collisions where the lead vehicle was reported as stopped by the NASS/CDS investigators. Table 15 shows the lead vehicle (LV) movement prior to the crash. The LV was stopped in 84 of the 96 cases or 88.5% of weighted collisions.

Table 15. Lead Vehicle (LV) Movement for EDR Rear-end Collisions

LV Movement	n	Freq.	%
LV Stopped	84	43,452	88.5
LV Moving at Slower Speed	12	5,645	11.5
Total	96	49,097	100

For the 84 LV stopped scenarios with braking, the TTC at brake initiation is listed in Table 16. Of drivers with braking, 92% applied the brakes within 2 seconds of the collision. For all cases, the mean TTC at brake activation was 1.18 s.

Table 16. Mean Time of Collision (TTC) at Brake Initiation for Times Prior to Collision at Brake Activation

Time Before Collision at Brake Initiation	n	Freq.	Nominal TTC (s)	Lower Bounds TTC (s)	Upper Bounds TTC (s)
Less than 1 s	18	9,027	0.53	0.22	0.79
1 to 2 s	53	31,154	1.21	0.88	1.49
2 to 3 s	7	663	1.97	1.68	2.24
3 to 4 s	3	1,847	2.41	2.23	2.55
4 to 5 s	3	760	3.72	3.39	4.04
Total	84	43,452	1.18	0.85	1.45

Figure 34 shows the TTC and time before the crash when braking initiated. If there was no braking before the crash, the TTC and time before the crash would be equal and the points would all fall on the diagonal line. The more braking and lower the speed and higher the braking deceleration, the further points will fall below the diagonal line. The largest proportion of crashes are clustered at a nominal time before the collision of -1.5 s, which corresponds to a -2 s as recorded on many of the GM EDR records. There are clusters corresponding to -0.75 s, -0.5 s, and -0.5 s due to the low time resolution of EDR pre-crash records (either 1 or 2 samples per second).

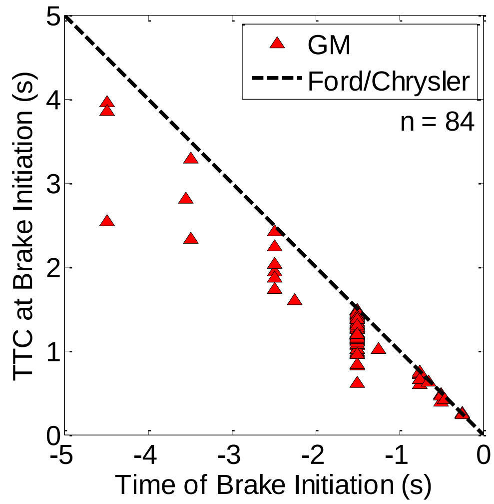


Figure 34. TTC and Time Before Crash at Brake Initiation for Lead Vehicle Stopped Crashes.

Figure 35 shows a histogram of the TTC at brake initiation with a lognormal distribution fit. A lognormal distribution has been used by past studies to model reaction times since these values are greater than 0 and are often skewed right. The mean and standard deviation of the lognormal fit are 0.0634 and 0.4646, respectively. The discretization between approximately 0.75 and 1 s was caused by the large time steps of the older EDRs in the sample. Our assumption is that with better time resolution this discretization would not appear. We do not believe it is indicative of a two distinct groups appearing in the data. Although the number of cases examined in this study is relatively low and the time discretization may affect the distribution fit, the lognormal fit appears to be a feasible for these data.

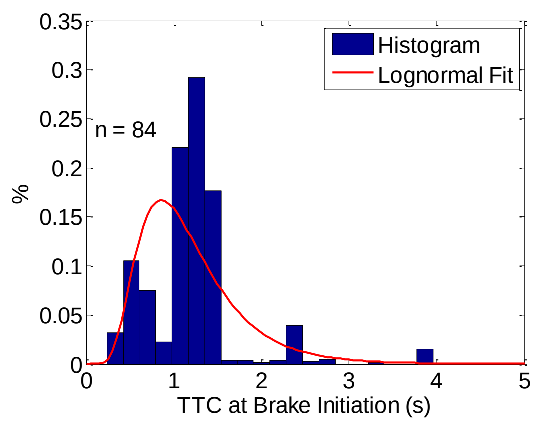


Figure 35. Histogram of TTC at Brake Initiation with Lognormal Distribution Fit.

One of the assumptions of the driver response model to FCAS is that the braking scenarios of "hard late" and "early weak" braking are equally as probable. In our proposed model, braking that occurs at a TTC before the driver would apply brakes in response to FCW is treated as steady state braking (see Figure 30 and Figure 31). The generic model of FCW used in this study delivers the warning to the driver at a TTC of 1.7 s. Figure 36 shows the average deceleration and TTC at brake initiation separated by a TTC of 1.7 s. Using the NASS/CDS sample weights, 19.5% of cases were considered early braking and 80.5% late braking. The weighted average deceleration for early braking was 0.12 g and for late braking was 0.38 g. This result confirms the magnitude of braking used in our driver response model (0.2 g for early and 0.4 g for late braking) are feasible. This data suggest that in those rear-end conflict situations that result in a crash, hard late braking is more common.

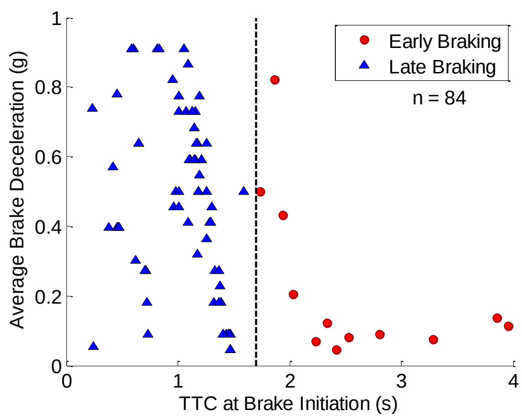


Figure 36. Average Brake Deceleration by TTC at Brake Initiation

3.4. DISCUSSION

The results of this study can be used in the design and evaluation of FCAS. False, or nuisance, alarms are a concern for system developers because they lead to drivers disabling the systems out of annoyance [94,95]. Table 17 shows the activation TTCs for one proposed FCAS and the corresponding percentiles for the EDR braking sample examined in this study. The FCW activation TTC of 1.7 s corresponded to the 80.5th percentile of drivers. Put differently, only 19.5% of drivers were already braking at a TTC of 1.7 s. This result shows that a warning delivered at this timing could be potentially useful to drivers because few would already be braking. Not addressed by this study, however, is how frequently the warning TTC is encountered in normal driving, i.e. non-emergency following situations, where the warning could be viewed as unnecessary. CIB, the autonomous braking function, should only intervene when almost no drivers are likely to begin braking. In the sample of EDR braking, only 10.3% of drivers braked at a TTC less than 0.45 s.

Table 17. Example Component Activation Times and Corresponding Percentiles of EDR Braking Sample

Component	Activation TTC (s)[1]	Corresponding Percentile of EDR TTC
FCW	1.7	80.5%
DBS	0.8	21.3%
CIB	0.45	10.3%

[1]*From Aoki et al., 2010*

The EDR pre-crash data used in this study has several limitations. First, the time step for the most common EDRs in the sample was 1 second. When most braking occurs in the last 2 seconds prior to the crash, this uncertainty in time may affect the results. The recently approved Part 563 rule became effective in September of 2012 and will affect EDR modules in the future U.S vehicle fleet [77]. This rule specifies the required data elements types that must be stored if a vehicle has an EDR. The rule requires all EDRs to record vehicle speed, brake switch status, and throttle for 5 seconds to 0 seconds before the collision with at least 2 samples per second. Some manufacturers, such as Chrysler that sample pre-crash data at 10 samples per second, may exceed the required sample time. The new rule will increase the time resolution of the future sample of EDRs. Another limitation is the time uncertainty of the EDRs caused by circular buffering of the data before the crash. Increasing the data sample rate would also reduce the time uncertainty.

As electronic stability control systems become more common, EDRs may also record steering wheel input prior to the crash. In the sample of 143 EDRs with pre-crash data, only 11 were able to store steering data. With such few EDRs with steering data, no conclusions of driver steering reaction could be made in this study. Previous studies have found that steering is relatively rare in rear-end collision avoidance [70].

3.5. CONCLUSION

In this chapter, we presented a general model for developing and deriving driver response models to active safety systems. As an example, we developed a model for driver braking response to a generic FCAS based upon experimental data. The model captures the different modes of operation of the system that interacts with when the driver applies the brakes. This response includes the simulation weights used to compute the number of crashes and injuries with the system. Next, a novel method for verifying parts of the driver braking response model using EDR data was presented. Of striking vehicle drivers, 28% had little or no brake input to the vehicle. In crashes that resulted in a moderate to fatal injury (MAIS2+), 64% of drivers applied little or no braking. For those drivers that did apply the brakes, the mean average braking deceleration was 0.40 g. The TTC at which braking was initiated was on average 1.18 s. The results of this study can be used to design and evaluate warning timings for active safety systems.

4. Models of Injury Risk in Crashes

4.1. INTRODUCTION

Many active safety systems not only prevent collisions but also mitigate the severity of those collisions that do occur. In order to determine the reduction in injuries from these systems, a model must be developed that relates the severity of a crash to expected injury outcomes.

One possible approach to developing an injury risk model is through detailed physics-based simulation models, e.g MADYMO or Finite Element (FE) models [100, 101]. These detailed models are extremely useful for detailed study of injury mechanism and design optimization of restraint systems. Detailed models are sensitive, however, to the boundary conditions of the simulations. In real-world collisions, details are often lacking. Important factors such as occupant dimension and seating position prior to the crash are often missing or not measured. Instead of a physics-based model, the approach in the current study is to use a statistical model of injury risk. A statistical approach is more suited to the data source used in this study, NASS/CDS.

The objective of this chapter is to develop a statistical model that describes the risk for injury to an occupant given the crash severity.

4.2. METHODOLOGY

The most common statistical technique for developing injury risk functions is binary logistic regression [102-111]. Binary logistic regression is a function that predicts the probability of an observation being in class 1 compared to class 2, e.g. the probability that an occupant is injured vs. not injured. Logistic regression is a generalized linear model that links predictors to the outcome via the logit function. Logistic regression models can be seen as dose-response models that correlate predictors to the probability of an outcome. For example, the risk of injury is the probability of injury, defined as:

$$P(\Delta V, belt\ use) = \frac{\#\ Injured\ Occupants}{\#\ Exposed\ Occupants} \qquad (1)$$

Consider data with N observations, each belonging to a class described by Y_i. Each observation has a vector of M features, X_i. The classes of all observations are described by Y, an N by 1 vector, and the features described by X, an N by M matrix. In logistic regression, a linear combination of predictors are linked to the probability of belonging to one class over the other by the logit function:

$$\ln \frac{p}{1-p} = \boldsymbol{\beta X} \tag{2}$$

where p is the probability of an event occurring. Solving for p yields the logistic function:

$$p(X) = \frac{1}{1+\exp(-\boldsymbol{\beta X})} = \frac{1}{1+\exp\big(-(\beta_0 + \beta_1 X_1 + \cdots + \beta_M X_M)\big)} \tag{3}$$

where $\beta_1, \ldots, \beta_M$ are the regression coefficients for each of the predictors $X_1, \ldots, X_M$. Coefficients are determined using maximum likelihood estimates in an iterative fashion, e.g. Fischer Scoring. The negative sign in front of the coefficient matrix is arbitrary but preserves the proportional relationship between the predictor and outcome. A positive coefficient indicates an increased probability of the event occurring with an increase in the predictor. Logistic regression is better suited for binary outcomes compared to ordinary linear regression because the logistic function is bounded by 0 and 1.
Logistic and linear regression analyses share many of the same properties. However, one key difference is that in logistic regression the errors in the model are described by a binomial distribution instead of a normal distribution as in linear regression [107].

Using logistic regression as a measure of injury risk is a well-established practice in the transportation safety literature [107-110]. The variable that is most correlated with injury risk in many of these studies is change in vehicle velocity during the collision, or ΔV. Unlike impact speed prior to a crash, ΔV is a measure of the momentum change during a crash. For example, there is greater injury risk of impacting a large tree at 40 mph compared to impacting a small bush at 40 mph. In this extreme example, the ΔV for the impact with the large tree would be larger than the ΔV for the impact with the bush. The next most critical factors in determining injury risk are seat belt use and the damage side of the impact. In general, side impacts have higher injury risk than frontal impacts, which have a higher risk than rear-end impacts. Other factors that can be considered in logistic regression models are occupant age, vehicle weight, and crash partner vehicle type.

The data source for fitting the logistic regression will be rear-end collisions from NASS/CDS. The predictors used in the injury models for the striking and struck vehicle are listed in Table 18. Past studies have found that the distribution of ΔV is skew right. As a result, we used the natural logarithmic transform of ΔV in our model to better conform with the assumptions of logistic regression [105]. In rear-end collisions, the occupant information of the struck vehicle driver is often missing. As a result, occupant age and sex is often missing. The struck vehicle driver experiences a rear collision, which drives the occupant into the seat back. As a result, seat belt use of the struck vehicle driver has less influence on injury risk than the seat belt use of the striking vehicle driver. Vehicles almost always have a driver but sometimes do not have passengers. Therefore, there is not enough injury data on passengers to compute separate risk curves. In this study, injury risk curves will only be developed for the driver of the vehicle.

Table 18. Predictor Variables Used for Logistic Regression Model for Striking and Struck Vehicle Drivers in Rear-end Collisions

Predictor (units)	Striking Driver	Struck Driver
log(ΔV) (log(kph))	☑	☑
Seat Belt (No/Yes)	☑	
Age (years)	☑	
Sex (F/M)	☑	

The functional form of the logistic regression for the striking vehicle driver is:

$$P(\Delta V, belt\ use) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \log(\Delta V) + \beta_2 (belt) + \beta_3 (age) + \beta_4 (sex))}} \quad (4)$$

where β_0, β_1, β_2, β_3, and β_4 are coefficients determined by the regression analysis. For seat belt use, the quantity $belt$ was equal to 1 for unbelted drivers, and -1 for belted drivers. For the sex variable, a female driver had a value of 1 and a male driver had a value of -1. Injury risk curves were developed based on the same set of cases identified for ΔV reduction analysis.

The software package SAS 9.2 (SAS Institute, Cary, NC) was used for the statistical analysis. The survey logistic procedure (*proc surveylogistic*) was used to account for variability caused by the complex sample design and weighting of cases in NASS/CDS. The outcome variable used in this study is if the driver of the vehicle is moderately to fatally injured (MAIS2+), as described in Chapter 2. Serious to fatal injury (MAIS3+) was presented in the target population for FCAS. For model fitting, however, there were not enough MAIS3+ cases to provide sufficient model fit. MAIS2+ injuries was used instead for this chapter.

4.3. RESULTS

4.3.1. Selected Cases

In Chapter 2, the target population of crashes from NASS/CDS was identified using the last 5 years of data available, 2007-2011. In order to increase the number of cases for modeling and simulation, in this chapter we will examine NASS/CDS years 1997 to 2011. As will be shown below, many of the variables needed for modeling and simulation are missing from the data. We included 15 years instead of 5 years to increase the number of cases for analysis. Our assumption is that rear-end collisions have not changed drastically in the last 15 years and that increasing the number of cases examined will decrease the variance in the logistic regression model.

Table 19 summarizes the number of all crash types and rear-end crashes in the two NASS/CDS year ranges. Both year ranges have approximately the same proportion of rear-end crashes with respect to all crashes (24.7% for 2007-2011 and 23.5% for 1997-2011). The target population for FCAS in Chapter 2 included rear-end collisions where the driver of the striking vehicle was going straight prior to the collision as well as those that were changing lanes, merging, or turning prior to the crash. In the sample, the majority of rear-end crashes, 94%, had a driver that had no maneuver prior to the crash. Further, some rear-end crashes resulted in damage to the striking vehicle that was not frontal damage. This could occur in circumstances where the leading vehicle was maneuvering prior to the crash, resulting in a sideswipe type crash. In this chapter, we will only examine this no-maneuver group of rear-end crashes that resulted in frontal damage to the striking vehicle.

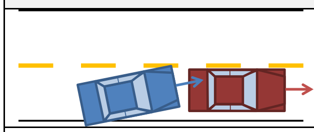
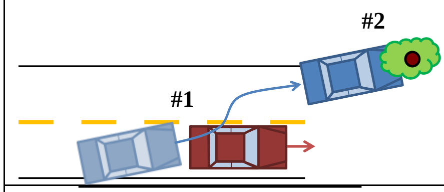
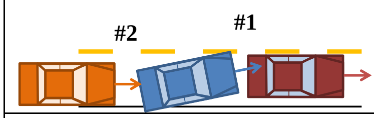
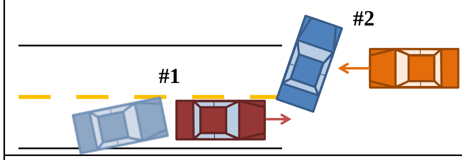
Table 19. Comparison of Rear-end Crash from NASS/CDS Years 2007-2011 and 1997-2011

	NASS/CDS Years			
	2007-2011		**1997-2011**	
Group	**n**	**Freq.**	**n**	**Freq.**
All Crashes	24,464	10,267,849	70,260	35,412,632
Rear-end Crashes	4,320	2,536,117	11,165	8,335,350
No Maneuver Rear-end Crashes	4,115	2,401,553	10,607	7,874,829
First Event Resulted in Frontal Damage	4,057	2,323,924	10,427	7,689,609

Table 20 summarizes the configurations in rear-end collisions. The most common configuration (93%) was a single event crash. Two frontal events, such as a rear-end followed by a crash with a fixed object, and a frontal followed by a rear event were less common. For ease of modeling both injury and the crash, we will only analyze single event crashes in this study. Multiple event crashes may increase injury risk for occupants. Furthermore, the crash reconstruction techniques used by NASS/CDS investigators are not able to reconstruct crash ΔV if there are multiple impacts to the same plane, e.g. two frontal events. The impact of this restriction is minor, however, since almost all rear-end crashes in this sample are single event crashes.

The injury risk model for the striking vehicle includes ΔV, driver seat belt use, and age as predictors. In the striking vehicle of rear-end collisions, restraints such as seat belts and airbags can affect injury outcome. In the struck vehicle, the occupant is driven into the seat structure and restraint presence does not affect injury as greatly. As a result, we restricted the striking vehicle to either 1) have a model year of 1998 or greater or 2) be equipped with an airbag. Model year 1998 corresponded to regulations that depowered frontal airbags in all passenger vehicles. Of those single event rear-end crashes, 6,110 cases corresponding to 4,378,253 collisions, or 61%, had airbags or were a model 1998 or greater vehicle.

Table 20. Configuration of Rear-end Crashes (NASS/CDS 1997-2011 No Maneuver Rear-end Crashes)

	Configuration	Freq.	%
	Single Event	7,159,287	93%
	Two Frontal Events	173,386	2%
	Frontal, then Rear Event	136,888	2%
	Frontal, then Side Event	75,905	1%
	All Other	144,144	2%
	Total	7,689,609	100%

4.3.2. Missing Information from NASS/CDS

Coded information is sometimes missing from NASS/CDS cases. In particular, the predictive variables used in the model of injury (ΔV, seat belt use, and age) can be missing. Additionally, the vehicle length and weight, used in the crash model in Chapter 5, can also be missing. This section summarizes the number of cases excluded because of missing values.

Table 21 summarizes the proportion of cases with missing information for either the striking or struck vehicle. Past studies on injury risk estimation have suggested removing case weights that are excessively large because these large weight cases add more variance into estimates than the bias caused by their removal [105]. Kononen suggested removing any cases from a NASS/CDS analysis that had a case weight greater than 5,000. In our analysis, we removed cases greater than the 99th percentile of case weights, which was in this case a weight of 6,037. Although not used for the injury risk model, the vehicle length and weight of both the striking and struck vehicle is needed for the crash severity model developed in Chapter 5. Overall, 41% of rear-end crashes had all the required information for this analysis. The crash ΔV was most commonly missing (46% of cases). For comparison, ΔV is missing for

54% of all vehicle records in NASS/CDS. In NASS/CDS, ΔV can be missing because the investigator was not able to measure the vehicle damage, e.g. if the vehicles were already repaired or disposed of. Driver seat belt status and age are only needed for the driver of the striking vehicle. When excluding high weight cases, the distribution of missing values does not appear to change greatly.

Table 21. Missing Data in Rear-end Crashes from NASS/CDS

				Weight Less than 6,037 (99%tile)		
Group	**n**	**Freq.**	**% of All Crashes**	**n**	**Freq.**	**% of All Crashes**
All Rear-end Crashes	**6,110**	**4,378,253**	**-**	**6,048**	**3,460,664**	**-**
Missing ΔV	2,911	2,020,501	46%	2,883	1,639,794	47%
Missing Vehicle Length	91	60,296	1.4%	91	60,296	1.7%
Missing Vehicle Weight	25	14,134	0.3%	25	14,134	0.4%
Missing Striking Vehicle Injury	1,137	787,238	18.0%	1,128	624,003	18.0%
Missing Striking Vehicle Driver Seat Belt Use	1,703	1,188,968	27%	1,685	893,387	26%
Missing Striking Vehicle Driver Age	1,099	771,013	18%	1,099	771,013	22%
Cases with All Information	**2,484**	**1,794,782**	**41%**	**2,459**	**1,427,499**	**41%**
No Struck Vehicle Occupant Record	1,221	1,208,456	67%	1,206	939,846	66%
Cases with All Striking and Struck Information	**1,263**	**586,326**	**33%**	**1,253**	**487,654**	**34%**

Information about the driver in the struck vehicle is missing more often than information about the striking driver. Out of the 2,459 cases with all information for the striking vehicle, in 1,206 cases there was no occupant record for the driver of the struck vehicle. This means there was no estimate of the struck vehicle driver's age, injury outcome, or seat belt use.

One hypothesis for the large number of cases with missing occupant information for the struck vehicle could be that the crash was not severe enough to cause large damage in the struck vehicle. If the investigator believed there was a low chance of the struck vehicle driver being transported to a medical facility, they may be less likely to attempt to retrieve medical records for that occupant. Excluding these crashes with missing struck vehicle occupant information may bias injury risk estimates because the crashes with struck occupant information may be more likely to result in injury. To test this hypothesis, we will examine two populations: 1) with all striking vehicle information (*n=2,459*) and 2) with all striking and struck driver information (*n=1,253*).

4.3.3. Univariate Characteristics of Single-Event Rear-end Crashes

As suggested by Kononen et al, ΔV should be log-transformed for use in a logistic regression model because its untransformed distribution does not follow a normal distribution [105]. Figure 37 compares the normal fits for the striking and struck vehicle ΔV. From visual inspection, the log-transformed data has a better normal fit than the untransformed data. The descriptive statistics for ΔV and log-transformed ΔV are shown in Table 23.

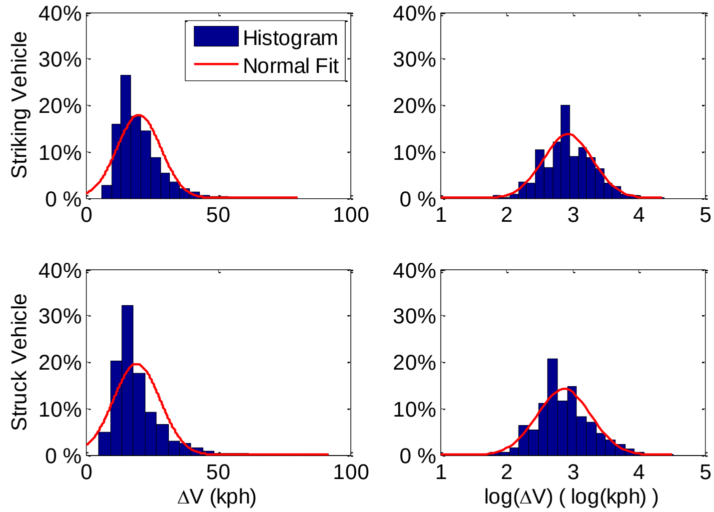


Figure 37. Comparison of Normal Fits for ΔV and Log-Transformed ΔV.

Table 22. Median, Mean, and Standard Deviation of ΔV and Log-transformed ΔV for Striking and Struck Vehicles in Rear-end Collisions

	Median		**Mean**		**Standard Deviation**	
Variable	**Striking**	**Struck**	**Striking**	**Struck**	**Striking**	**Struck**
ΔV (kph)	17.84	16.65	20.15	19.30	0.34	0.40
log(ΔV) (log(kph))	2.88	2.81	2.93	2.87	0.017	0.020

Table 23 shows the distribution of belt use and sex for the driver of the striking and struck vehicles. Because information about the struck vehicle driver was often missing, 29% of seat belt use and 66% of driver sex was missing in the struck vehicle. For the known seat belt use 90% of drivers in the struck vehicle were belted and for known driver sex 48% of drivers were male.

Table 23. Distribution of Belt Use and Sex for the Striking and Struck Vehicle Drivers.

		Striking Vehicle		Struck Vehicle	
Variable	**Category**	**Freq.**	**%**	**Freq.**	**%**
Belt Use	Belted	1,262,773	88%	417,971	29%
	Unbelted	164,727	12%	44,799	3%
	Missing	0	0%	964,730	68%
	Total	1,427,499	100%	1,427,499	100%
Sex	Male	751,211	53%	234,423	16%
	Female	676,289	47%	253,205	18%
	Missing	0	0%	939,872	66%
	Total	1,427,499	100%	1,427,499	100%

The mean and median ages of drivers are shown in Table 24. Struck vehicle drivers were slightly older than striking vehicle drivers on average. Both distributions were slightly skew right. A transforms of age did not greatly affect a normal fit, as it did in the case of ΔV.

Table 24. Mean and Median Age for Drivers in the Striking and Struck Vehicles.

Measure	**Striking**	**Struck**
Mean Age	35.9	38.6
Median Age	31.1	36.1

Table 25 shows the number of MAIS2+ injured drivers in the striking and struck vehicle. In the striking vehicle 2.3% of drivers were injured. The struck vehicle was again missing approximately two-thirds of driver information. In crashes with known struck driver information, 2.8% of drivers were injured. This difference in proportions when including and excluding struck vehicles with missing information illustrates the potential bias issues.

Table 25. Number of MAIS2+ Injured Drivers in the Striking and Struck Vehicle.

	Striking Vehicle		Struck Vehicle	
	Freq.	**%**	**Freq.**	**%**
MAIS2+ Driver	32,223	2.3%	13,621	1.0%
Not Injured	1,395,276	97.7%	465,334	32.6%
Missing	0	0%	948,545	66.4%
Total	1,427,499	100%	1,427,499	100%

4.3.4. Logistic Regression

Table 26 shows the results from the logistic regression model fit to the chance of a driver having an MAIS2+ injury for the group of collisions with all striking vehicle information and for the group with all striking and struck vehicle information. Coefficients for each variable are listed next to "Coeff." and the odds ratio is listed next to "O.R." Odds ratios describe how much more likely the outcome, i.e. an injured driver, is given a unit increase in the parameter. For categorical variables, i.e. seat belt use and sex, an odds ratio is the odds of the outcome of one value of the variable compared to the other. For example, the odds ratio for a driver being unbelted is 2.76, meaning an unbelted driver is 2.76 times more likely to be injured thank a belted driver in a similar collision. Because the ΔV in the model is transformed by a natural logarithm, the odds ratio represents the increase in odds given an e-fold (i.e. 2.72) increase, for example from 20 kph to 54 kph. The c-statistic is a measure of model fit. A c-statistic of 1 indicates a perfect fit to the data and a value of 0.5 suggests the model is no better than a random guess. The results show that the two models are very similar, as seen by both the coefficient and odds ratio values even though the second model has half the raw number of cases and less than a third of the weighted frequency of the first. Examination of the 95% confidence interval for coefficients and odds ratios, the two models overlap in almost every category. This suggests that missing information in the struck vehicle does not greatly impact the injury risk prediction in the striking vehicle.

Table 26. Logistic Regression Models for Striking Vehicle Driver Injury (MAIS2+) for Cases with All Striking Vehicle Information and All Striking and Struck Vehicle Information

Value		All Striking Information			All Striking and Struck Information		
		Value	95% Confidence Int.		Value	95% Confidence Int.	
n		2,459			1,253		
Freq.		1,427,499			487,654		
Intercept	Coeff.	-13.30	-16.14	-10.45	-12.00	-15.51	-8.50
Log(ΔV)	Coeff.	2.99	2.21	3.76	2.70	1.73	3.67
	O.R.	19.8	9.1	43.1	14.9	5.7	39.4
Driver Unbelted	Coeff.	0.508	0.183	0.832	0.408	-0.126	0.941
	O.R.	2.76	1.44	5.28	2.26	0.78	6.57
Age	Coeff.	0.0124	-0.0026	0.0273	0.0092	-0.0070	0.0254
	O.R.	1.01	1.00	1.03	1.01	0.99	1.03
Sex	Coeff.	0.2872	0.0065	0.5679	0.0926	-0.2514	0.4366
	O.R.	1.78	1.01	3.11	1.20	0.61	2.40
C-statistic		0.798			0.757		

Table 27 shows the results from the logistic regression for struck vehicle driver injury. Because of the large amount of missing driver information, i.e. age and sex, the model only used ΔV as a predictive variable. For the first model using cases with all striking vehicle information, if the struck vehicle was missing a driver record, it was assumed the driver was uninjured. Unlike the model for the striking vehicle, excluding the cases with missing struck vehicle information greatly affected the results. For example, the first model would predict a 4.9% risk for in a crash with a ΔV of 40 kph compared to a 7.5% risk for injury by the second model.

Table 27. Logistic Regression Model for Struck Vehicle Driver Injury (MAIS2+) for Cases with All Striking Vehicle Information and All Striking and Struck Vehicle Information.

Value		All Striking Information			All Striking and Struck Information		
		Value	95% Confidence Int.		Value	95% Confidence Int.	
n		2,459			1,253		
Freq.		1,427,499			487,654		
Intercept	Coeff.	-14.51	-19.33	-9.68	-11.25	-16.39	-6.11
Log(ΔV)	Coeff.	3.13	1.72	4.54	2.37	0.86	3.88
	O.R.	22.8	5.6	93.4	10.7	2.4	48.5
C-statistic		0.813			0.759		

Given the results of two logistic regression models fit to the two populations, we determined the population with all striking vehicle information should be used for analysis. First, the striking vehicle injury, where the majority of the injuries in rear-end crashes occurred, are unaffected by the removal of cases with missing struck vehicle information. Second, the model for the struck vehicle driver with the all striking vehicle information population is a conservative estimate of injury risk. Excluding all cases with missing information may bias the struck vehicle population. Thus the benefits estimates for the struck vehicle presented in Chapter 5 will be greater if we used the population with all striking and struck vehicle information.

Table 28 shows the regression results for the striking vehicle driver. P-values were estimated using a Wald chi-squared test. Note that driver age was the only coefficient that was not significant to the $\alpha = 0.05$ level. It was left in the model because of its known association with injury risk. The point estimate still suggests that older occupants are more at risk for injury.

Table 28. Logistic Regression Results for Probability of an Injured Driver (MAIS2+) in the Striking Vehicle

	Coefficient	p-value	Odds Ratio	95% Confidence Intervals	
Intercept	-13.298	< 0.0001	-	-	-
ΔV	2.986	< 0.0001	19.8	9.095	43.106
Driver Unbelted	0.508	0.0022	2.76	1.443	5.279
Age	0.012	0.1046	1.012	0.997	1.028
Sex	0.287	0.0449	1.776	1.013	1.013

The regression results for the struck vehicle driver are shown in Table 29. Both coefficients were significant predictors of injury risk.

Table 29. Logistic Regression Results for Probability of an Injured Driver (MAIS2+) in the Struck Vehicle

	Coefficient	p-value	Odds Ratio	95% Confidence Intervals	
Intercept	-14.506	< 0.0001	-	-	-
ΔV	3.127	< 0.0001	22.804	5.569	93.388

Figure 38 shows the injury risk functions for the striking and struck vehicle driver. For the striking vehicle, the curves shown are for a 35-year-old male. The ΔV in the graphs are shown as a linearly increasing function in the figure, but the risk is calculated using the log of the ΔV. The highest risk of injury is for an unbelted striking vehicle occupant, followed by a belted striking vehicle and struck vehicle driver. For example, at a ΔV of 40 kph, the risk for injury is 16.4% for an unbelted striking vehicle driver, 6.6% for a belted striking vehicle driver, and 4.9% for a struck vehicle driver.

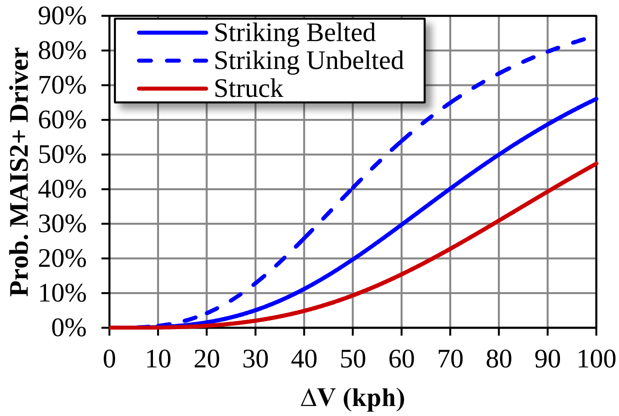


Figure 38. Injury Risk Functions for Striking and Struck Vehicle Drivers in Rear-end Collisions. The striking vehicle curves are for a male driver with age 35 years. ΔV is shown as a linear function, but is log-transformed for the calculation of injury risk.

Figure 39 shows a cumulative distribution of the actual and predicted number of MAIS2+ injured drivers in the striking vehicle. The actual and predicted number of injured drivers was 32,223.

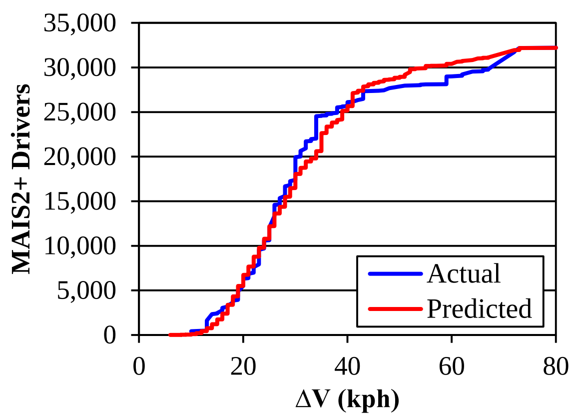


Figure 39. Actual and Predicted Number of Injuries in the Striking Vehicle.

The actual and predicted number of injured drivers in the struck vehicle is shown in Figure 40. The predicted number of injured drivers shows more variation from the actual curve compared to the striking vehicle model. The total number of injured occupants still matches between the actual and predicted (13,621).

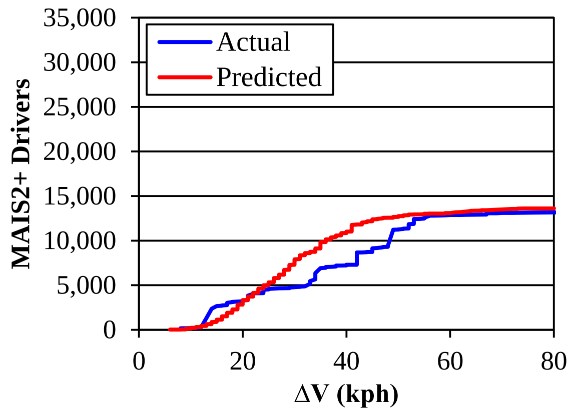


Figure 40. Actual and Predicted Number of Injuries in the Struck Vehicle.

4.4. DISCUSSION

One of the main limitations of the NASS/CDS database is that ΔV is missing in over half of all vehicles in the database. The common practice is to use complete case selection and discard any cases that having missing information for the logistic regression analysis. Ignoring this missingness in the model, however, is inefficient and can bias estimates [112]. The best proposed method for accounting for missing data is through Multiple Imputation, first proposed by Rubin in 1987 [113]. Multiple Imputation uses a latent class model to predict the value of missing variables using the values of known variables for each observation. A central assumption of this methodology is that the variables are Missing Completely at Random (MCAR).

Kononen et al. attempted to replace missing values of ΔV in NASS/CDS using multiple imputation for use in their logistic regression analysis [105]. They found that using a dataset that imputed the missing values for ΔV in 32% of their cases, the coefficient for ΔV was much smaller than a model using only the complete cases. They decided not to use the imputed dataset, citing literature that suggested multiple imputation would be less effective when a large portion of the cases had missing values. Also at issue with using multiple imputation for replacing missing values of ΔV is that the variables are not missing at random. For example, multiple impacts to the same damage plane prevent investigators from reconstructing ΔV. The NHTSA provides imputed variables for their General Estimates System (GES) and Fatality Analysis Reporting System (FARS) databases. It is beyond the scope of this dissertation to explore imputation, but analysts of NASS/CDS would benefit greatly from further guidance from NHTSA on possible methods for imputing missing values in NASS/CDS.

4.5. CONCLUSION

In this chapter, a methodology for generating injury risk functions was presented. The model used data available from NASS/CDS investigations (injury outcome, ΔV, seat belt use, occupant age) to fit logistic regression that predicted injury risk. These models will be used to predict the reduction in the number of seriously injured drivers due to FCAS using the predicted ΔV as if the system were active in Chapter 5.

5. Crash Severity Model and System Benefits

5.1. OBJECTIVE

Having identified the target population, driver model, and injury model in the previous chapters, the objective of this chapter is to introduce methods for determine the crash severity reduction in crashes. The crash severity metric reconstructed in NASS/CDS is the vehicle change in velocity during the collision, ΔV. In this chapter we will present a novel method for predicting the ΔV in a crash after the application of additional braking, e.g. as a result of FCAS activation. Using this ΔV calculation method and the methodology developed in the previous chapters, we will also predict the number of crashes and injured drivers prevented due to FCAS in the U.S. vehicle fleet.

5.2. METHODOLOGY

5.2.1. Reconstruction of Crash ΔV in NASS/CDS

The change in velocity during a crash, ΔV, is a critical measure of crash severity. The ΔV can be estimated given the impact speeds, orientations, weights, and approximate stiffnesses of the vehicles involved in a crash using what is called planar impact mechanics crash reconstruction [114, 115]. Planar impact mechanics use impulse and momentum equations as their basis. Planar impact mechanics is considered an acceptable method for crash reconstruction and is used in crash reconstruction software, e.g. PC-Crash [116]. Crashes in NASS/CDS are investigated in retrospect, possibly days or weeks after the crash occurs. The vehicle post-crash location and orientation is rarely known for crashes investigated for NASS/CDS and any other evidence from the crash scene is also fleeting. It is extremely difficult, therefore, to estimate impact speeds and impact orientations required for traditional planar impact mechanics methods in NASS/CDS cases.

To estimate the ΔV without knowledge of initial vehicle speeds, an alternative solution was developed that was known as the Calspan Reconstruction of Accident Speeds on the Highway (CRASH) program. This method was developed by Campbell and McHenry and was first introduced in 1974 [117].

Specifically, the damage algorithm, a part of the CRASH program, correlates the crush observed after the crash and the energy absorbed by the vehicle, which can be used to compute ΔV. A version of this algorithm is still used today by NASS/CDS crash investigators in a program called WinSmash [118]. A full derivation of the damage algorithm of CRASH3 is available in the CRASH3 user's manual [119]. We will present this derivation below as context for the novel computation of ΔV after brake activation presented in the next section.

Consider a collinear collision where the crash forces only pass through the vehicle centers of mass as shown in Figure 41. The vehicles in this collision only move in the x-direction and both have linear stiffnesses, k_1 and k_2, and masses m_1 and m_2. The distances x_1 and x_2 are the displacements of the center of masses of the vehicles.

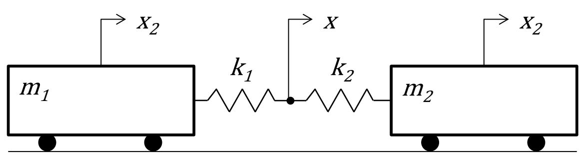


Figure 41. Model of Collinear Collision.

Consider the equations of motion of the vehicles:

$$m_1\ddot{x}_1 = -\left(\frac{k_1k_2}{k_1+k_2}\right)(x_1 - x_2) \tag{1}$$

$$m_2\ddot{x}_2 = \left(\frac{k_1k_2}{k_1+k_2}\right)(x_1 - x_2) \tag{2}$$

Let $\delta = x_1 - x_2$. Equation 1 and 2 can be combined to give

$$\ddot{\delta} + \left(\frac{k_1k_2}{k_1+k_2}\right)\left(\frac{m_1+m_2}{m_1m_2}\right)\delta = 0 \tag{3}$$

This differential equation can be solved for the maximum relative displacement, δ_{max}, as

$$\delta_{max} = \left(\dot{x}_{1,0} - \dot{x}_{2,0}\right)\sqrt{\frac{(k_1+k_2)m_1m_2}{k_1k_2(m_1+m_2)}} \tag{4}$$

where $\dot{x}_{1,0}$ and $\dot{x}_{2,0}$ are the impact velocities of vehicle 1 and 2, respectively. Rearranging terms we have

$$\left(\dot{x}_{1,0} - \dot{x}_{2,0}\right) = \sqrt{\frac{(k_1 + k_2)m_1 m_2 (\delta_{max})^2}{k_1 k_2 (m_1 + m_2)}} \tag{5}$$

Let $\delta_1 = x_1 - x$ and $\delta_2 = x_2 - x$, which are the compression of both springs with respect to the collision interface, x. The forces in each spring must be equal: $k_1\delta_1 = k_2\delta_2$. And by definition, $\delta_1 + \delta_2 = \delta$. Combining these relationships with equation 5, we get

$$\left(\dot{x}_{1,0} - \dot{x}_{2,0}\right) = \sqrt{\frac{(k_1 + k_2)m_1 m_2 (k_1\delta_1^2 + k_2\delta_2^2)}{k_1 k_2 (m_1 + m_2)}} \tag{6}$$

The energy absorbed in each spring is $E_1 = \frac{1}{2}k_1\delta_1^2$ and $E_2 = \frac{1}{2}k_2\delta_2^2$. Substituting into equation 6 yields

$$\left(\dot{x}_{1,0} - \dot{x}_{2,0}\right) = \sqrt{\frac{(k_1 + k_2)m_1 m_2 (2)(E_1 + E_2)}{k_1 k_2 (m_1 + m_2)}} \tag{7}$$

There are two phases of the collision considered in this model: 1) the approach and 2) rebound. The approach period is the time between contact to maximum crush, i.e. δ_{max}. The assumption of this algorithm is that at maximum crush, the contact point between the two vehicles reaches a common velocity, V_c. After common velocity is reached, the vehicles rebound until they separate. The total change in velocity is the impact speed minus the speed at separation. Now consider the conservation of moment from impact to maximum crush or during the approach period:

$$m_1\dot{x}_{1,0} + m_2\dot{x}_{2,0} = (m_1 + m_2)V_c$$

$$V_c = \frac{m_1\dot{x}_{1,0} + m_2\dot{x}_{2,0}}{m_1 + m_2} \tag{8}$$

The change in kinetic energy during the approach period, E_A, is the difference between the initial kinetic energy of the system, KE_0, and the kinetic energy of the systems at common velocity, KE_c: $E_A = KE_0 - KE_c$. Solving for E_A yields:

$$E_A = \frac{1}{2}m_1\dot{x}_{1,0}^2 + \frac{1}{2}m_1\dot{x}_{2,0}^2 - \frac{1}{2}(m_1 + m_2)V_c^2$$

$$E_A = \frac{1}{2}\left(\frac{m_1 m_2}{m_1 + m_2}\right)\left(\dot{x}_{1,0} - \dot{x}_{2,0}\right)^2 \tag{9}$$

We can solve equation 8 to find the change in velocity during the approach period, ΔV:

$$\Delta V_1 = V_c - \dot{x}_{1,0} = -\left(\frac{m_2}{m_1 + m_2}\right)\left(\dot{x}_{1,0} - \dot{x}_{2,0}\right)^2 \tag{10}$$

and

$$\Delta V_2 = V_c - \dot{x}_{2,0} = -\left(\frac{m_1}{m_1 + m_2}\right)\left(\dot{x}_{1,0} - \dot{x}_{2,0}\right)^2 \tag{11}$$

Using equation 9, we can replace the relative velocity and rearrange terms:

$$\Delta V_1 = \sqrt{\frac{2E_A m_2}{m_1(m_1 + m_2)}} \tag{12}$$

and

$$\Delta V_2 = \sqrt{\frac{2E_A m_1}{m_2(m_1 + m_2)}} \tag{13}$$

Using similar equations, the change in velocity during the rebound phase can also be found. These formulae involve a coefficient of restitution and the total energy absorption during the crash, E_T. The procedure that is used to compute ΔV in NASS/CDS, however, does not consider restitution or the rebound phase. Equation 12 and 13 are the basis for the ΔV reported in NASS/CDS cases. The accuracy of ΔV as a result of these assumptions is a continuing topic of research. Previous research has found that WinSmash ΔV values are on average 10%-15% lower than their nominal values [120-126]. This is an inherent limitation in the methodology used by the NASS/CDS investigators. Because the current study will use the ΔV reported in NASS/CDS as a starting point for computations, our proposed method will also assume no rebound.

The key to the damage algorithm is estimating the absorbed energy in the crash. For NASS/CDS investigations, this is accomplished by correlating the measured static crush observed after the crash with the absorbed energy. The method for this correlation is an empirical observation that the crush is linearly related to the square root of the energy absorbed per unit length of damage, as shown in Figure 42. The slope, d_1, and intercept, d_0, of this line are found from measured crush and computed energy absorption from staged crash tests. The early version of WinSmash used categorical stiffness coefficients based upon the vehicle type. An improved WinSmash algorithm was introduced in 2008 that used stiffnesses for individual makes and models to improve estimates [124].

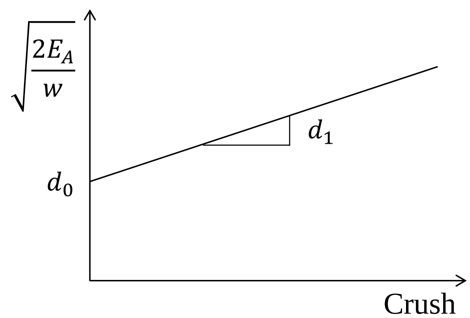


Figure 42. Correlation between Measured Vehicle Crash and Absorbed Energy.

Real-world collisions can be assumed to be planar impacts in many cases, but they are certainly rarely collinear. A non-collinear crash is shown in a diagram of a rear-end collision in Figure 43. For non-collinear collisions, additional values are needed to compute ΔV using the CRASH3 damage algorithm: the damage center location, P, the Principal Direction of Force ($PDOF$), and the moment arm of the resultant crash force, h. The damage center location is estimated using the damage width and depth. The PDOF is estimated by the investigator by examination of the vehicle damages. The moment arm of the resultant crash force is computed using vehicle geometry, the damage location, and Center of Gravity (CG) location.

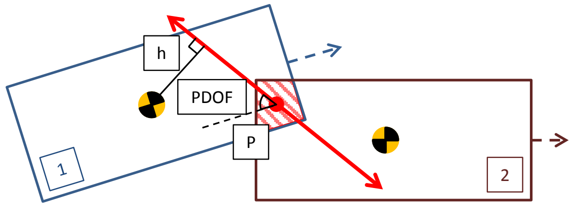


Figure 43. Model of Non-Collinear Collision.

The acceleration at the CG of vehicle 1, $\ddot{x}_1$, is a function of the acceleration at the crash center, $\ddot{x}_p$ and the rotational acceleration, $\ddot{\theta}_1$:

$$\ddot{x}_1 = \ddot{x}_p + h_1\ddot{\theta}_1 \tag{14}$$

Summing the moments about the CG of vehicle 1 gives

$$F_x h_1 = -I_1\ddot{\theta}_1 = R_1^2 m_1 \ddot{\theta}_1$$

$$\ddot{\theta}_1 = -\frac{F_x h_1}{R_1^2 m_1} \tag{15}$$

where F_x is the longitudinal crash force and R_1 is yaw radius of gyration of the vehicle. Using equation 14 and 15, we can solve for $\ddot{x}_p$:

$$\ddot{x}_p = -\frac{F_x}{m_1}\left(\frac{R_1^2 + h_1^2}{R_1^2}\right) \tag{16}$$

Therefore, the acceleration at the CG is

$$\ddot{x}_1 = -\frac{F_x}{m_1} = \left(\frac{R_1^2}{R_1^2 + h_1^2}\right)\ddot{x}_p \tag{17}$$

In the damage algorithm, the term $\frac{R_1^2}{R_1^2+h_1^2}$ is called the effective mass coefficient, γ_1, and relates the change in velocity at the crash center, ΔV_p, and change in velocity at the CG, ΔV_1:

$$\Delta V_1 = \gamma_1 \Delta V_p \tag{18}$$

Using a similar approach than for a collinear collision, the final crash ΔV's can be computed as

$$\Delta V_1 = \sqrt{\frac{2\gamma_1 E_A}{m_1\left(1+\frac{\gamma_1 m_1}{\gamma_2 m_2}\right)}} \tag{19}$$

and

$$\Delta V_2 = \sqrt{\frac{2\gamma_2 E_A}{m_2\left(1+\frac{\gamma_2 m_2}{\gamma_1 m_1}\right)}} \tag{20}$$

The central assumption in this method is that the direction of the crash force, PDOF, is constant during the collision. This assumption allows for the effective mass coefficient to account for the proportion of crash force that results in linear and rotational accelerations. Rose *et al.* found this was a valid assumption in crash where the collision is relatively short [127]. The calculations are also sensitive to the investigator's estimates of PDOF, which have been found to vary by as much as +/- 20° [128].

5.2.2. Computation of Reduced ΔV due to Additional Pre-Crash Braking

To compute the crash severity reduction of FCAS, collisions were reconstructed using the information in NASS/CDS to predict the crash severity which would have occurred if there had been additional braking due to system activation. Consider a rear-end collision where the striking vehicle (vehicle 1) collides with a second vehicle (vehicle 2). The ΔV for this collision for vehicle 1 is defined as

$$\Delta V_1 = V_{12,0} - V_c \tag{21}$$

where $V_{12,0}$ is the velocity of vehicle 1 with respect to vehicle 2 at impact and V_c is the common velocity achieved following the collision. The change in velocity of vehicle 2 is simply V_c. Therefore, the sum of the two ΔVs yields the impact velocity:

$$\Delta V_1 + \Delta V_2 = V_{12,0} - V_C + V_C = V_{12,0} \tag{22}$$

Now consider a collision where the driver of vehicle 1 increases the braking magnitude from a_{t0} to a_{t1} and again to a_{t2} prior to the collision. This scenario is akin to how drivers using a FCAS experience an increase in braking in response to a warning and again prior to the collision via autonomous pre-crash braking. A diagram of the vehicle deceleration before and after increased braking is shown in Figure 44. The increases in braking level occur at a jerk authority of *j*. The jerk authority is the maximum rate at which deceleration can be increased by the braking system and is a function of the brake actuators. The first braking pulse starts at a time to collision TTC_1 and the second at TTC_2. The first braking pulse has duration of t_1 and the entire braking pulse has duration of t_2.

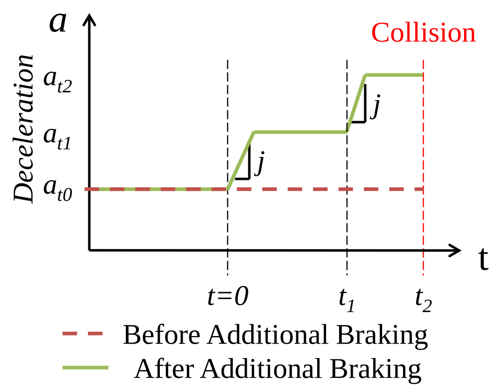


Figure 44. Braking Deceleration before and after Additional Braking.

The speed of vehicle 1 at the time of the first brake activation (TTC_1), $V_{12,1}$, can be found using a kinematic relationship:

$$V_{12,1} = a_{t0}TTC_1 + \sqrt{(a_{t0}TTC_1)^2 + (V_{12,0})^2} \tag{23}$$

Examining the first braking pulse and integrating the acceleration of the vehicle yields the velocity of the vehicle at t_1, which is equal to the vehicle velocity at the start of the second braking pulse, $V_{12,2}$:

$$v(t_1) = V_{12,2} = -a_{t1}t_1 + \frac{(a_{t1} - a_{t0})^2}{2j} + V_{12,1} \tag{24}$$

Integrating once more yields the position at t_1:

$$x(t_1) = -\frac{1}{2}a_{t1}t_1^2 + \left(\frac{(a_{t1} - a_{t0})^2}{2j} + V_{12,1}\right)t_1 - \left(\frac{(a_{t1} - a_{t0})^3}{6j^2} + V_{12,1}TTC_1\right) \tag{25}$$

The second braking pulse starts at an activation time of TTC_2, which corresponds to a position, x_1:

$$x(t_1) = -V_{12,2}TTC_2 \tag{26}$$

Due to symmetry in the equations, the kinematics of the vehicle are described similarly to (24) and (25) for the second braking pulse. The resulting equations are quadratic, allowing for the braking times of the first and second pulses, t_1 and t_2, to be solved algebraically.

The reduction in velocity created by the braking can be found by integrating the deceleration pulse:

$$\mathrm{P}_{\mathrm{brake}} = \frac{a_{t2}^2 - a_{t0}^2}{2j} + a_{t1}\left(t_1 - \frac{a_{t1} - a_{t0}}{j}\right) + a_{t2}\left(t_2 - \frac{a_{t2} - a_{t1}}{j}\right) \tag{27}$$

Using conservation of momentum, the change in velocity after braking, ΔV_1^*, can be derived in terms of the change in velocity without additional braking, ΔV_1, using an approach similar to the CRASH3 algorithm:

$$\Delta V_1^* = \Delta V_1 - \frac{\gamma_1\gamma_2 m_2}{\gamma_1 m_1 + \gamma_2 m_2}\mathrm{P}_{\mathrm{brake}} \tag{28}$$

This method is based on the velocity of vehicle 1 relative to vehicle 2. This method can be used if the struck vehicle is accelerating or decelerating at a constant rate. The accelerations (a_0, a_1, and a_2) simply become the relative accelerations:

$$a_{12} = a - a_s \tag{28}$$

The development of the closed-form solutions above makes that assumption that the braking time before and after additional braking is equal. After the additional braking, the time between the onset of braking and the crash will be larger than that before additional braking. This assumption was made so that a simple closed from solution for change in ΔV could be found, in equation 28. The assumption makes our predicted severity reductions conservative, as the additional braking time would increase the effectiveness of the systems.

5.2.3. Modeling System Limitations

The maximum vehicle braking deceleration is restricted by the road surface type and conditions. Table 30 lists nominal maximum braking deceleration for different surfaces and conditions [129-132]. Surface type and condition were determined from NASS/CDS variables. Vehicles were determined to be sliding based on pre-crash maneuver and pre-crash impact stability. Unknown surface types were assumed to be pavement and unknown surface condition was assumed to be dry. If vehicle stability was unknown, it was assumed the vehicle was tracking prior to the collision. Because vehicles with FCAS would feature an Anti-Lock Brake System (ABS), striking vehicles were assumed to achieve the maximum possible braking deceleration with FCAS activation, regardless of lock-up that occurred before FCAS. The braking decelerations for each simulation were adjusted to reflect the maximum braking deceleration based on surface type, condition, and stability.

Table 30. Maximum Braking Deceleration in g for Different Surface Types and Conditions [129-132]

Surface Condition	Braking (no lockup)	Sliding (all wheels locked)
Dry Pavement / Asphalt / Concrete	0.8	0.65
Wet Pavement / Asphalt / Concrete	0.7	0.55
Snow	0.4	0.25
Ice	0.15	0.075
Dry Gravel/Dirt	0.7	0.6
Wet Gravel/Dirt	0.6	0.5

Most FCAS do not activate at low vehicle speeds. The Forward Collision Warning (FCW) and crash imminent braking (CIB) systems were assumed to activate at relative vehicle speeds greater than 15 kph (9.32 mph). The dynamic brake support (DBS) component was assumed to activate at relative vehicle speeds greater than 30 kph (18.6 mph). If the warning threshold was not met at the time of system activation, the case had no system activation and thus no benefit. If the DBS threshold was not reached, braking was adjusted accordingly to match the driver's input. If the CIB threshold was not reached, the braking level was maintained at its previous level until the collision.

5.2.4. Benefits Assessment of FCAS Algorithms

As described in Chapter 3, we assessed the potential effectiveness of an FCAS with several combinations of components: 1) FCW only, 2) FCW and DBS, and 3) FCW, DBS, and CIB. Figure 27 summarizes the TTC activation times for each component.

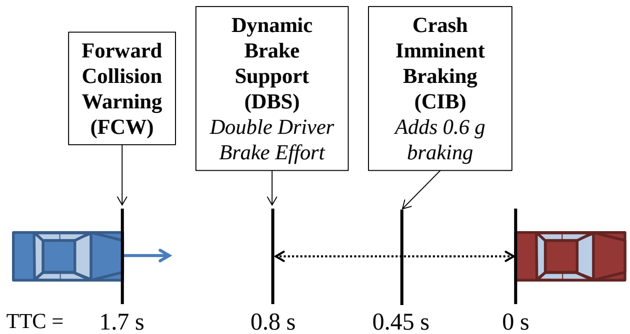


Figure 45. Activation Timing of FCAS Components Leading to a Crash [93].

Each rear-end crash from NASS/CDS with all available information required for the simulations were simulated once with each of the three FCAS algorithms. The results of the simulation was the reduction in ΔV for both the striking and struck vehicle. The simulations also predict which crashes could have been avoided. Using this reduced ΔV and the injury risk model developed in Chapter 4, the number of injured occupants was predicted and compared with the number of predicted injured drivers before the system was active.

The high level of additional braking when FCAS components activate may reduce the impact speed of a collision but could also potentially greatly alter to seated posture of unbelted occupants. Especially in airbag deployment crashes, there is concern that high levels of braking could move unbelted occupants closer to the steering wheel, which could have negative effects when the airbag deploys. There is limited discussion in the literature on the potential tradeoffs between reducing kinetic energy in the crash via braking and possible negative effects of creating an out of position occupant. From publically available information from manufacturers, there is no indication that any production systems modify or suppress pre-crash braking one or more of the occupants are unbelted.

Preliminary laboratory crash tests comparing a vehicle with no pre-crash braking and autonomous braking prior to the impact were conducted in Germany [133]. The test was run at the European New Car Assessment Test (EuroNCAP) test conditions of a 64 kph (40 mph) full frontal impact into a rigid barrier. After the CIB activated, the barrier impact speeds of the vehicles was between 50.7 kph and 40.4 kph. Both driver and right front passenger were belted and the vehicle was equipped with reversible belt pretensioners that deployed with the FCAS autonomous braking. The results of the tests showed that most injury metrics for the driver and right front passenger were reduced after system activation. Peak right front passenger chest deceleration, however, was increased after pre-crash braking. This test series did not include unbelted occupants, however. Although this test series is a limited sample, it suggests further investigation of restraint performance during pre-crash braking. One study simulated occupant response in collisions with automated braking with a human model with seat belt activation, but did not compare the injury risk with a crash of greater severity without pre-crash braking [134].

Because of the unknown interaction between unbelted occupant position due to pre-crash braking and injury risk, we will not predict injury risk benefits for unbelted occupants in the striking vehicle in this study. It is possible that unbelted occupants could benefit from pre-crash braking due to the reduction in kinetic energy in the collision. Excluding unbelted occupants is thus a conservative estimate of benefits of FCAS systems in the vehicle fleet.

5.3. RESULTS

5.3.1. Characteristics of Selected Cases

The selected cases for this analysis were the same as those presented in Chapter 4: 2,459 rear-end collisions extracted from NASS/CDS years 1997 to 2011 that corresponded to 1,427,499 weighted collisions. These selected cases excluded multi-event rear-ends, those missing data needed for simulation (e.g. ΔV), non-airbag equipped striking vehicles, and those with extreme weights greater than the 99th percentile of weights in the sample.

Almost all collisions occurred on concrete or asphalt (99.6%). Of all crashes, 83% occurred on a dry road surface, 15% on a wet surface, and 2% on snow or ice. Table 31 summarizes the driver pre-crash avoidance braking maneuvers in the striking and struck vehicle. In the striking vehicle, 14% of all drivers had missing values for the pre-crash maneuver. These missing values were simulated as no and braking cases with simulations weights proportional to the number of no braking/braking cases in the population as discussed in Chapter 3. Most drivers in the striking vehicle were applying the brakes according to the NASS/CDS investigators (71%). In the struck vehicle, however, most drivers were not braking or were standing still and thus had zero acceleration prior to the crash. Data was not missing from the struck vehicle driver because if the avoidance maneuver variable was missing, driver avoidance maneuver could be inferred from the accident type variable, i.e. standing still, moving at a lesser speed, or decelerating.

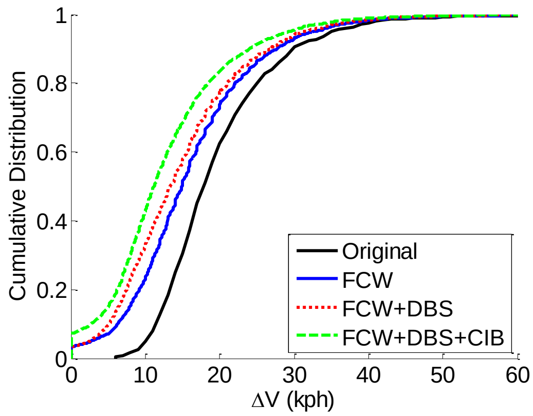
Table 31. Pre-Crash Maneuvers for Striking and Struck Vehicles in Rear-end Collisions

	Striking Vehicle		Struck Vehicle	
Pre-Crash Maneuver[1]	**Freq.**	**%**	**Freq.**	**%**
No Braking	356,548	29.0%	1,310,323	91.79%
Braking	655,786	53.4%	111,337	7.80%
Braking with Lockup	212,823	17.3%	630	0.04%
Accelerating	2,351	0.2%	5,209	0.36%
Total	1,227,509	100%	1,427,499	100%

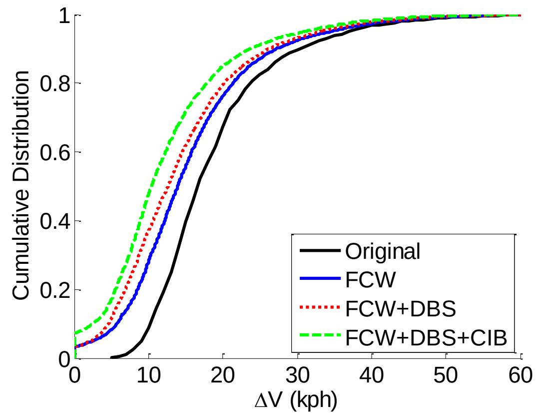
[1]For striking driver, 199,990 drivers had missing braking status (14.0% of all)

5.3.2. Reduction in Crash Severity and Injury

The reduction in crash ΔV for each algorithm is shown in Figure 46. The distributions for the striking and struck vehicle are very similar because most of the collisions involved two passenger vehicles. Because the ΔV of two vehicles that impact each other are related by the ratios of their masses, vehicles that have similar masses will have similar ΔV. Adding more components to the FCAS algorithm increased their effectiveness. The FCW only and FCW+DBS algorithms had similar effectiveness while the FCW+DBS+CIB algorithm reduced ΔV more than the other two. This result suggests that drivers that received a warning were able to apply near the maximum braking by the time DBS activated in our model, providing only marginal additional benefits with the addition of DBS. The addition of the autonomous CIB systems, however, was able to mitigate crashes where there would have been little or no driver braking prior to the crash, resulting in further reduction in population ΔV.



Striking Vehicle



Struck Vehicle

Figure 46. Cumulative Distribution of ΔV for FCAS Algorithms.

Table 32 tabulates the prevented collisions and median ΔV in the original populations and after FCAS simulations. The FCW and FCW+DBS algorithms had similar number of crashes prevented. In our generic FCAS, the activation threshold for DBS was 30 kph compared to 15 kph for FCW and CIB. As a result, at low relative vehicle speeds where drivers could potential avoid collisions, the FCW only and FCW+DBS algorithms performed similarly. As shown above, the striking and struck vehicle had on average similar reductions in ΔV for a given system. Adding more FCAS components increased the reduction in crash severity.

Table 32. Crashes Prevented and Median Striking and Struck Vehicle ΔV and Per cent Reduction for Simulations with FCAS (NASS/CDS 1997-2011)

		Median ΔV, those that occurred			
Group	**% Prevented**	**Striking ΔV (kph)**	**Struck ΔV (kph)**	**% Reduction Striking**	**% Reduction Struck**
Original	-	17.84	16.65	-	-
FCW	3.39%	15.11	14.21	15.3%	14.6%
FCW+DBS	3.43%	13.94	12.89	21.8%	22.6%
FCW+DBS+CIB	7.20%	11.78	11.06	34.0%	33.6%

The reduction in ΔV caused by the addition of an FCAS will lead to a reduction in the number of injured drivers, shown in Table 33. Striking vehicle drivers had a slightly higher reduction in injured drivers than the struck vehicle because injury risk in the striking vehicle is greater than that of the struck vehicle for the same ΔV.

Table 33. Predicted Number of Injured Drivers for FCAS Simulations (NASS/CDS 1997-2011)

	MAIS2+ Injured Drivers		% Reduction	
	Striking (belted)	Struck	Striking (belted)	Struck
Original	23,497	13,621	-	-
FCW	15,852	10,571	32.0%	21.8%
FCW+DBS	13,971	9,497	40.4%	30.1%
FCW+DBS+CIB	10,302	7,404	54.9%	44.4%

5.3.3. Extension of Benefits to Entire Vehicle Fleet

The simulations of FCAS benefits were only conducted using a subset of rear-end collisions. Cases were most often excluded because of missing reconstructed ΔV or striking vehicle driver seat belt status. To estimate the expected fleet-wide benefits of FCAS, we assumed that the effect of FCAS in the entire population of single event rear-end collisions would be the same as than in those that we simulated. Table 34 shows the expected number of crashes that FCAS could have prevented in the entire vehicle fleet. For this analysis we considered all rear-end collisions that occurred between 2007 and 2011, the last 5 years of data available. We excluded multi-event rear-end crashes and those that did not involve frontal damage as the first harmful event for the striking vehicle. Annually in NASS/CDS, rear-end collisions are approximately 21% of all collisions. Out of an average of 2,053,570 tow-away collisions per year from NASS/CDS, the three FCAS algorithms could prevent 0.71%, 0.72%, and 1.52% of all collisions per year, respectively.

Table 34. Number of Collisions Prevented in All Rear-end Collisions Prevented by FCAS

Group	Rear-end Collisions	FCW	FCW + DBS	FCW + DBS + CIB
Single Event Rear-end with no Maneuver (2007-2011 n = 3,548)	2,162,038	-	-	-
% Prevented from Simulations	-	3.39%	3.43%	7.20%
Crashes Prevented 2007-2011	-	73,400	74,115	155,771
Crashes Prevented Per Year	-	14,680	14,823	31,154
Annual % of all NASS/CDS		0.71%	0.72%	1.52%

The reduction in the number of injured drivers in rear-end collisions due to FCAS activation is shown in Table 35. Annually, the MAIS2+ drivers in the striking and struck vehicle of rear-end collisions account for 6.2% of all MAIS2+ drivers in NASS/CDS. Using the simulated reduction in MAIS2+ drivers in both the striking and struck vehicles, the three algorithms could prevent 1.73%, 2.24%, and 3.13% of the 124,454 MAIS2+ drivers in NASS/CDS annually.

Table 35. Number of MAIS2+ Injured Drivers in the Striking and Struck Vehicles of Rear-end Collisions Prevented by FCAS

Category	Group	Rear-end Collisions	FCW	FCW + DBS	FCW + DBS + CIB
MAIS 2+ Drivers 2007-2011	Striking Vehicle (Belted, n = 111)	23,290	-	-	-
	Struck Vehicle (n = 105)	15,098	-	-	-
% MAIS2+ Injury Reduction	Striking Vehicle (Belted)	-	31.97%	40.43%	54.90%
	Struck Vehicle	-	21.83%	30.15%	44.40%
Injuries Prevented 2007-2011	Striking Vehicle (Belted)	-	7,446	9,415	12,786
	Struck Vehicle	-	3,296	4,552	6,704
MAIS2+ Drivers Prevented per Year	Striking Vehicle (Belted)	-	1,489	1,883	2,557
	Struck Vehicle	-	659	910	1,341
	Both	-	2,148	2,793	3,898
% of all MAIS2+ Drivers Prevented	Striking Vehicle (Belted)		1.20%	1.51%	2.05%
	Struck Vehicle		0.53%	0.73%	1.08%
	Both		1.73%	2.24%	3.13%

5.3.4. Economic Benefit of FCAS

To estimate the annual economic benefit of FCAS in the U.S. vehicle fleet we considered the cost savings from both 1) property damage only (PDO) crashes and 2) injured driver crashes prevented. In our model, the proportion of crashes prevented would reduce the amount of property damage. The number of injured drivers (MAIS2+) prevented would result in additional economic benefit from the reduction in lost wages and medical costs. Table 36 summarizes the economic cost for a PDO and a MAIS 2 injury crash [135]. These costs were developed considering both short and long-term effects of crashes. Considered were both medical related (emergency services, market productivity, insurance, workplace, legal) and non-injury related (travel delay, property damage) costs associated with different severity crashes. To estimate the cost of PDO and MAIS 2 injury crashes in current economic prices, the Consumer Price Index (CPI) inflation were used to convert between year 2000 and 2013 U.S. dollars [136].

Table 36. Unit Cost of Crashes in Year 2000 and 2013 US Dollars [135].

Crash Severity	Total Cost (2000 USD)	Total Cost (2013 USD)
Property Damage Only	$2,532	$3,425
MAIS 2	$66,820	$90,391

To compute economic benefits, we used the annual predicted number of crashes and injured drivers prevented and applied the cost of PDO and MAIS 2 crashes to each. In our injury risk model, we predicted the number of drivers that had MAIS 2 or greater injuries (MAIS2+), which includes drivers with MAIS injuries of level 2 through 6 and those who were fatally injured. The majority of drivers labeled as MAIS2+ had a MAIS 2 injury level (74% in both striking and struck vehicles). Thus for our economic analysis, we assigned the cost of a MAIS 2 injury level to those MAIS2+ prevented collisions.

Table 37 summarizes the approximate economic benefit of the three FCAS algorithms. The cost of prevented collisions was less than that of the benefit of reducing the number of injured drivers. In total, the three systems could prevent between $184 and $338 million of economic costs associated with crashes per year. This economic analysis is only an estimate of economic benefit based upon prevented collisions and injury crashes. Not considered in this analysis is the cost of implementing the system in all vehicle in the U.S. fleet, which is beyond the scope of this study.

Table 37. Annual Economic Benefit of FCAS Algorithms in 2013 U.S. Dollars.

	Prevented		Cost Savings		
System	**PDO**	**MAIS2+**	**PDO**	**MAIS2+**	**Total**
FCW	14,680	1,489	$ 50,278,855	$ 134,613,212	$ 184,892,068
FCW+DBS	14,823	1,883	$ 50,769,103	$ 170,212,269	$ 220,981,372
FCW+DBS+CIB	31,154	2,557	$ 106,703,319	$ 231,141,059	$ 337,844,378

5.4. DISCUSSION

Table 38 compares past benefits estimates studies of FCAS to the current study. Many of the studies were included in a review by Bayly *et al.* as part of the European Commission's TRACE project [33]. From the results of past studies, a wide range of potential effectiveness, both in reduction in crashes and injury, had been found. One possible explanation is that modeled FCAS can have widely different designs. Factors that affect results include how early the systems activate and at what level. For the FCW studies, the systems in both the NHTSA (1996) and McLaughlin (2007) studies had TTC activations that were well above the 1.7 s TTC activation used in the current study. As a result, the number of predicted collisions prevented for these systems was much higher than in the current study. Many studies assumed overall effectiveness values and simply applied them to the target populations (e.g. Regan *et al.*, and McKeever *et al.*). These methodologies generally produced more conservative benefits estimates compared to their simulated counterparts. The studies that are most similar in methodology to the current study are those done by Sugimoto (2005) and Van Auken (2011). Both these studies used vehicle dynamics simulations in conjunction with a model to of driver reaction to predict crash severity reduction and then injury risk curves to determine injury effectiveness.

Table 38. Comparison of Past FCAS Benefits Estimates Projects with Current Study

Study	System	Benefits
NHTSA (1996) [137]	FCW	• 48% rear-end crashes prevented (warning TTC average of 3.3 s)
Regan (2002) [138]	FCW	• 7% rear-end crashes prevented (Assumed effectiveness, acceptability, severity shift)
McLaughlin (2007) [41]	FCW	• 50%-70% of rear-ends could be avoided (three systems with average warning TTC from 3.3 s to 3.6 s, with activation speed thresholds)
Kusano (current study)	FCW	• 3.39% rear-end crashes prevented • 32.0% reduction in MAIS2+ drivers in striking vehicle • 1.73% reduction of all MAIS2+ drivers (striking and struck driver in rear-end)
Page (2005) [139]	FCW+DBS	• 11% reduction in injuries for all crash types (including pedestrian crashes, assumed brake assist could reduce brake application time by 50%)
Busch (2004) cited in Bayly *et al.*	FCW+DBS	• 5.1% reduction in injuries for passenger vehicles
Kusano (current study)	FCW+DBS	• 3.43% rear-end crashes prevented • 40.4% reduction in MAIS2+ drivers in striking vehicle • 2.24% reduction of all MAIS2+ drivers (striking and struck driver in rear-end)
McKeever (1998) [140]	FCW+DBS+CIB	• 9.1% reduction in injuries (Assuming 48% reduction factor for all rear-end crashes)
Sugimoto *et al.* (2005) [141]	FCW+DBS+CIB	• 38% rear-end crashes prevented • 44% reduction in fatal rear-ends • Based on production system (no activation parameters provided)
Van Auken *et al.* (2011) [37]	FCW+DBS+CIB	• 8.3% of all crashes prevented • 3.7% of all fatalities prevented • No activation parameters provided (CIB applied 0.6 g of braking)
Anderson et al. (2012) [38]	FCW+DBS+CIB	• 48% reduction in all injury crashes (TTC for autonomous braking from 3.0 to 1.5 s)
Bühne *et al.* (2012) and Bálint *et al.* (2013) [142-143]	FCW+DBS+CIB	• 20% reduction in slight (MAIS2) injured occupants in rear-end collisions (used average speed reduction in staged crash tests to predict speed reduction)
Kusano (current study)	FCW+DBS+CIB	• 7.20% rear-end crashes prevented • 54.9% reduction in MAIS2+ drivers in striking vehicle • 3.13% reduction of all MAIS2+ drivers (striking and struck driver in rear-end)

The generic FCAS we created a model of for this study activated later than other FCAS systems on the market. There is concern among system developers that alerting the driver earlier will greatly increase the incidence of false, or nuisance, alarms, which could lead to user annoyance and eventual deactivation of the system by the user. One way to combat false alarms is to move the activation times of the FCAS components closer to the collision. The tradeoff of this design decision, however, is that there is less time for the system to intervene and thus very few collisions were prevented. Even though the number of prevented crashes is low, however, the generic system modeled for this study showed great potential in mitigating injuries in rear-end collisions.

5.5. CONCLUSIONS

This thesis developed a novel methodology for using real-world crash database in "microscopic" rather than "macroscopic" simulations to determine the expected fleet-wide benefits of a proposed active safety system. The main benefits of the proposed methodology is that it 1) is based upon nationally representative samples of real-world crashes and 2) simulates the specific dynamics of each crash and the resulting reduction in the severity of collisions due to activation of a proposed system. This dissertation examined three FCAS algorithms: 1) FCW only, 2) FCW and DBS, and 3) FCW, DBS, and CIB. The FCW activated at a TTC of 1.7 s. The DBS doubled driver braking effort starting at a TTC of 0.8 s. Finally the CIB increased braking by 0.6 g starting at 0.45 s TTC. We predict that these three algorithms could prevent 3.39%, 3.43%, and 7.20% of all rear-end collisions, respectively. The prevented collisions and reduction in crash severity would lead to a reduction in the number of injured drivers (MAIS2+) of 32% for FCW, 40% for FCW and DBS, and 55% for FCW, DBS, and CIB for belted drivers in the striking vehicle. Slightly less effectiveness was found for the struck vehicle driver. In terms of all injured drivers annually, the three algorithms could prevent 1.73%, 2.24%, and 3.13% of all injured drivers (MAIS2+) annually including both striking and struck vehicle injury reductions. In total, the three systems could prevent between \$184 and \$338 million of economic costs associated with crashes per year. The results of these studies are directly applicable to regulators and vehicle manufacturers who are performing cost-benefit analysis of a proposed system.

6. Conclusions

6.1. STUDY CONCLUSIONS

6.1.1. Chapter 1 – Study Approach

This dissertation has presented research that developed a methodology for determining societal benefits from new active safety systems yet to be widely deployed in the vehicle fleet. The objective of this method was to forecast the number of crashes and injuries that would be avoided if a proposed active safety system were to be deployed throughout the U.S. vehicle fleet. A focus of the research was the simulation of real-world collisions on a case-by-case basis. Past studies often assumed overall system effectiveness and applied this effectiveness to all applicable cases macroscopically, ignoring the specifics of each crash. The current research performed "microscopic" simulations of individual cases extracted from real-world crash databases. This is challenging because of the lack of information on individual cases which is recorded in these databases. Another unique goal of this approach was to be able to quickly simulate a large number of real-world crashes. Past studies have either painstakingly reconstructed and simulated a small population or used Monte Carlo methods as a surrogate for a population estimate. The current research introduced a method in which a large representative sample of collisions is able to be simulated given the operation of the system.

Forward Collision Avoidance Systems (FCAS) was used throughout this dissertation as an example system. FCAS are one of several systems that are available on production vehicles. The framework developed herein, however, can be readily adapted to predict benefits for other systems, such as Lane Departure Warning (LDW) systems or other proposed active safety systems.

Predicting societal benefits for such active safety systems has several tasks, each of which was detailed in a chapter of this dissertation, as shown in Figure 4. The tasks are: 1) identifying the target population, 2) developing a model of driver reaction to the system, 3) developing a model to predict injury reduction, and 4) developing a model for crash severity reduction with the system. These components rely on each other and can be combined to predict both the number of crashes and injury prevented by a proposed system.

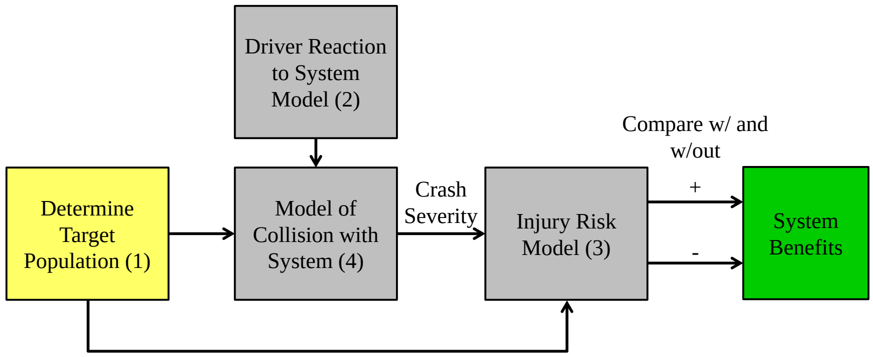


Figure 47. Method for Predicting Active Safety System Benefits

6.1.2. Chapter 2 –Target Populations of Active Safety Systems from Crash Databases

In this chapter we presented novel crash scenarios that describe the pre-crash configuration in crashes from real-world crash databases. These scenarios can be applied to these databases to identify the target populations for active safety systems. We identified the target population for three emerging active safety systems: Forward Collision Warning (FCW), LDW, and Vehicle-to-Vehicle/Vehicle-to-Infrastructure (V2V/V2I) systems. We used three nationally representative databases maintained by NHTSA to identify target populations: NASS/GES, NASS/CDS, and FARS. FCW was applicable to the largest number of exposed occupants (31%), but was only applicable to 6% of serious injury crashes and 7% of fatal crashes. LDW, on the other hand, was only applicable to 14% of all crashes but was applicable to 39% of serious injury and 43% of fatal crashes. V2V/V2I systems were applicable to 19% of all crashes, 23% of serious injury, and 15% of fatal crashes. In total, the pre-crash scenarios that these three systems could potentially mitigate were 60% of seriously injured occupants and 65% of fatal crashes, representing 3.3 million crashes and 18,367 fatal crashes annually.

Using a fourth database, the NMVCCS, we estimated the critical factors that lead to collisions with applicable pre-crash scenarios. Because NMVCCS investigators visited the scene of the crash before it was cleared by first responders, it contains a better estimate of crash cause than the other NHTSA crash databases, which are investigated retrospectively. We found that 53% FCW, 24% of

LDW, and 51% of V2V/V2I applicable scenarios were caused by driver distraction. These findings from NMVCCS were similar to past studies that investigated distraction in rear-end and road departure crashes using naturalistic data. This is an important finding because current active safety systems which rely on warning the driver will be most effective in mitigating crashes caused by distraction. Adjusting for distraction, these active safety systems could potentially mitigate approximately 1 in 5 crashes in the U.S., including serious injury and fatal crashes. Annually, this is 1.1 million all severity, 14,000 serious injury (MAIS3+), and 6,352 fatal crashes.

6.1.3. Chapter 3 – Development of Driver Reaction Models to Active Safety Systems

In this chapter, we presented a general model for developing and deriving driver response models to active safety systems. As an example, we developed a model for driver braking response to a generic FCAS based upon experimental data. The model captures the different modes of operation of the system that interacts with when the driver applies the brakes. This response includes the simulation weights that apply population distributions to determine how likely a braking response would be in the general population. These weights are used to compute the number of expected crashes and injuries with and without the system.

Next, a novel method for verifying parts of the driver braking response model using Event Data Recorder (EDR) data was presented. We examined a set of 143 crashes from the NASS/CDS database that had an EDR that recorded pre-crash vehicle speed, brake application, and throttle information downloaded from the striking vehicle in rear-end collisions. Of striking vehicle drivers, 28% had little or no brake input to the vehicle according to the EDR. In crashes that resulted in a moderate to fatal injury (MAIS2+), 64% of drivers applied little or no braking. For those drivers that did apply the brakes, the mean average braking deceleration was 0.40 g. The time to collision (TTC) at which braking was initiated was on average 1.18 s. In our model of driver brake response to an FCAS, we simulated two types of brake response: a driver who applied the brakes late and hard; and a driver who applied the brakes early but too weak to avoid the collision. Using the EDR data, we found that approximately 80% of drivers fell into the late and hard braking category and 20% in the early weak category. We used this result to derive simulation weights for these two braking scenarios used in our benefits estimate model. The EDR data also confirmed the TTC brake application and brake magnitude we used in our model, which agreed with past driving simulator and naturalistic driving studies.

6.1.4. Chapter 4 – Models of Injury Risk in Crashes

An injury risk function, which predicts the probability of injury given independent variables related to the severity of the crash and occupant characteristics, was used to estimate the reduction in injured occupants after an active safety function is deployed. In this chapter we developed injury risk curves using logistic regression and NASS/CDS data for rear-end collisions. The outcome the model predicted was if the driver of the striking or struck vehicle was seriously injured or not. Serious injury was defined as a driver who sustained a maximum abbreviated injury score (MAIS) of two or greater or was fatally injured (MAIS2+). The independent, or predictor, variables in the logistic regression model for the striking vehicle driver were crash change in velocity (ΔV), seat belt use, and occupant age. For the struck vehicle driver, only ΔV was used. Since the struck vehicle experiences a rear impact, driver seat belt status is less predictive of injury outcome because the seat back is the main loading mechanism in vehicles struck from the rear. In NASS/CDS, injury information and driver age information was missing in a large number of cases (66%) and thus was excluded from the model. We showed that the models fit the measured data very well, predicting within 1% the number of seriously injured drivers in the sample for both the striking and struck vehicle.

6.1.5. Chapter 5 – Crash Severity Model and System Benefits

We first introduced a methodology for computing what the crash ΔV would have been had there been additional braking due to an FCAS. Using the momentum-impulse crash reconstruction techniques used to reconstruct collisions in NASS/CDS, we derived a novel closed form solution for the new ΔV with additional braking. Using the driver model developed in Chapter 3, this mathematical crash model would determine the reduction in crash severity. Using the injury risk model developed in Chapter 4, the benefits of a proposed FCAS were derived.

This dissertation examined three FCAS algorithms with varying components: 1) FCW only, 2) FCW and dynamic brake support (DBS), and 3) FCW, DBS, and crash imminent braking (CIB). The FCW activated at a TTC of 1.7 s. The DBS doubled driver braking effort starting at a TTC of 0.8 s. Finally the CIB increased braking by 0.6 g starting at 0.45 s TTC.

We predict that these three algorithms could prevent 3.4%, 3.4%, and 7.2% of all rear-end collisions, respectively. The prevented collisions and reduction in crash severity would lead to a reduction in the number of injured drivers (MAIS2+) of 32% for FCW, 40% for FCW and DBS, and 55% for FCW, DBS, and CIB for belted drivers in the striking vehicle. Similar but slightly smaller effectiveness was found for the struck vehicle driver. In terms of all injured drivers annually, the three algorithms could prevent 1.7%, 2.2%, and 3.1% of all injured drivers (MAIS2+) annually including both striking and struck vehicle injury reductions. In total, the three systems could prevent between $184 and $338 million of economic costs associated with property damage and injury per year.

6.2. CONTRIBUTIONS TO LITERATURE

The research in this dissertation was presented in a large number of scholarly peer-reviewed conferences and journal publications, which are summarized in Table 39. All papers were authored solely by Kusano and Gabler. In total, 8 papers have already been published, 3 of which were accepted into refereed journals. An additional paper based upon the work in Chapter 2 of this dissertation is in preparation for the journal Traffic Injury Prevention. In addition to the scholarly publications, work related to parts of this dissertation was used to prepare 10 research reports for a 2-year collaborative research project with Toyota Motor Corporation and Toyota Engineering & Manufacturing North America.

Table 39. Publications Stemming from Dissertation Research by Kusano and Gabler

Dissertation Chapter	Peer-Reviewed Paper
2	• "Target Population for Injury Reduction from Pre-Crash Systems," *SAE Technical Paper Series* (2010) [144] • "On-Scene Determination of Driver Crash Causation and Avoidance Maneuvers in Rear-end Collisions," in *Proceedings of the 3rd International Conference on Road Safety and Simulation* (2011) [65] • "Identification of Target Populations for Current Active Safety Systems using Driver Behavior," in *Proceedings of the 2012 IEEE Intelligent Vehicles Symposium* (2012) [66] • "Comprehensive Pre-Crash Scenarios for Identifying Target Populations for Current and Future Active Safety Systems," *Traffic Injury Prevention***
3	• "Method for Estimating Time to Collision at Braking in Real-World, Lead Vehicle Stopped Rear-End Crashes for Use in Pre-Crash System Design," *SAE International Journal of Passenger Cars – Mechanical Systems* (2011)* [78] • "Real-world Driver Crash Avoidance Maneuvers in Rear-end Collisions using Event Data Recorders," In *Proceedings of the 4th International Conference on Road Safety and Simulation* (2013) [145]
4	• "Potential Occupant Injury Reduction in Pre-Crash System Equipped Vehicles in the Striking Vehicle of Rear-end Crashes," *Annals of the Advances in Automotive Medicine* (2010)* [145] • "Injury Mitigation in the Collision Partners of Pre-collision System equipped Vehicles in Rear-end Collisions," in *Proceedings of the 2011 IEEE Intelligent Transportation Systems Conference* (2011) [147]
5	• "Potential Effectiveness of Integrated Forward Collision Warning, Pre-Collision Brake Assist, and Automated Pre-Collision Braking Systems in Real-world, Rear-end Collisions," In *Proceedings of the 22nd International Conference on the Enhanced Safety of Vehicles* (2011) [148] • "Safety Benefits of Forward Collision Warning, Brake Assist, and Autonomous Braking Systems in Rear-end Collisions," *IEEE Transaction on Intelligent Transportation Systems* (2012)* [149]

**Denotes refereed journal publication*

***Denotes submitted/proposed refereed journal*

6.3. RESEARCH DIRECTIONS

The results of these studies are directly applicable to regulators and vehicle manufacturers who are performing cost-benefit analysis of a proposed system. As stated throughout the dissertation, the major benefit of the methodology we developed is that it takes a microscopic simulation approach (i.e. individual crashes) to model macroscopic effects (i.e. expected fleet-wide safety benefits). With all emerging crash avoidance systems, the interaction between the driver and system is key to its effectiveness. Studies that extrapolate effectiveness by relying upon a limited set of test track or driving simulator experiments risk misrepresenting that actual system's performance in the field. Although real-world crash databases are challenging data sources because many data elements are unknown or are only known to a superficial level, using what valuable data is collected to estimate system benefits should yield better results that assuming an overall effectiveness level in all crashes.

The main challenges overcame by this dissertation, and thus possibly its greatest contribution, is how to effectively account for unknown or shallow data. These novel methods we developed are interdisciplinary in nature, drawing from fields such as injury biomechanics, crash reconstruction, statistics, and vehicle handling. For example, the investigators note if the striking vehicle driver applied the brakes or not to avoid the collisions. Not recorded or reconstructed was the brake timing or brake magnitude likely in a crash imminent situation. To overcome this data shortcoming, we used EDR data to quantify the response of 143 drivers that all were involved in tow-away severity collisions. Another challenge was taking the ΔV reconstructed by NASS/CDS investigators and predicting what the ΔV would have been had there been additional braking. To solve this problem, we employed crash reconstruction techniques that were rooted in the methodology used by the NASS/CDS reconstruction software WinSmash.

Despite all the hurdles overcame in this research, there remain numerous challenges and potential improvements related to this research. The main limitation of this and many other benefits estimates studies is that driver response to crash imminent situations is extremely complex and not easily modeled. We leveraged EDR data and past naturalistic and driving simulator studies to formulate a model of how a driver would react to a rear-end following situation. The main parameters in this model are reaction time and brake deceleration. In our model, these parameters were fixed for all vehicle speeds. Speed, however, has been suggested to play a role in brake reaction [150]. Another parameter that may affect driver reaction to rear-end collision is age. On one hand, old age may increase reaction times. There is also evidence that younger drivers are involved in rear-end crashes at higher rates than other age groups [70]. In the studies that we used to formulate driver reaction time, there were no quantifiably significant differences between age groups. Some research has also suggested that drivers have drastically different reaction and following behavior, regardless of demographic data [151]. A better understanding of driver avoidance maneuvers in crash imminent situations would greatly improve the models used in the current methodology.

Our methodology assumed 100% penetration and 100% acceptance and use by drivers. In a survey of 500 Volvo owners with advanced safety features, the Insurance Institute for Highway Safety (IIHS) found that 89% of drivers always drove with FCW activated, compared to only about 60% that always had LDW active [94]. Systems are not effective if they are deactivated and annoyance with the system can lead users to distrust and deactivate systems [95]. Our model did not take acceptance into account because this data has not been tabulated for a large number of drivers. If the IIHS survey is an indication, however, it appears acceptance of FCW is relatively high, being higher than that of LDW.

The model we developed has many components (i.e. driver, crash, injury model) derived from various sources (e.g. NASS data, naturalistic data). Each of these individual models has its own uncertainty and thus the uncertainty of the entire model is a combination of each of these individual uncertainties. Although we did not perform this analysis, using traditional statistical definitions of uncertain may not be a useful effort because in many of the models utilize small datasets resulting in high standard errors. The stratified and clustered sample design of NASS/CDS surely exasperates these high variance estimates. The result would most likely be error bounds for system effectiveness that include 0 and 100%. Future research should develop a methodology that could determine the sensitivity of model components to the end benefits estimates.

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