BIOLOGICALLY INSPIRED CONNECTED ADVANCED DRIVER ASSISTANCE SYSTEMS

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BIOLOGICALLY INSPIRED CONNECTED ADVANCED DRIVER ASSISTANCE SYSTEMS

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To St. Joseph

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LIST OF SYMBOLS AND ABBREVIATIONS

A	Acceleration for the Optimization in Chapter 6
α	Acceleration
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving Systems
a_i	Max Acceleration Change for Vehicle i
AV	Autonomous Vehicles
α_{xn}	Deceleration of a Vehicle Based on Tire Longitudinal Cohesion
a_1	Vehicle 1 Acceleration
a_2	Vehicle 2 Acceleration
BICADAS	Biologically Inspired Connected Advanced Driver Assistance Systems
CV	Connected Vehicles
d	Distance Between Vehicles
d_i	Distance Between Vehicles
E	Emergency Vehicle Status for the Optimization in Chapter 6
e_1	Vehicle 1 Emergency Status
e_2	Vehicle 2 Emergency Status
F	Force
FARS	Fatality Analysis Reporting System
FSLDPT	Full-Size Light-Duty Pickup Trucks
g	Gravity
IIHS	Insurance Institute for Highway Safety
m	Mass

NHTSA	National Highway Traffic Safety Administration
t	Time (seconds)
UAV	Unmanned Ariel Vehicle
UGV	Unmanned Ground Vehicle
USDOT	United States Department of Transportation
USV	Unmanned Surface Vehicle
UUV	Unmanned Underwater Vehicle
UxV	General Unmanned Vehicle
V	Velocity for the Optimization in Chapter 6
v	Velocity
v_0	Initial Velocity
Δv	Change in Velocity
v_{1i}	Initial Velocity of Vehicle 1
v_{2i}	Initial Velocity of Vehicle 2
v_{1f}	Final Velocity of Vehicle 1
v_{2f}	Final Velocity of Vehicle 2
VIN	Vehicle Identification Number
VLC	Visual Light Communication
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
V2X	Vehicle to either Infrastructure or Vehicle
w_i	Archimedean Weights
φ_x	Coefficient of longitudinal cohesion between the tires and the ground
$\bar{x}$	Array of Values (subscripts denote position in array)
x	Position

x_0 Initial Position

γ Dead angle (blind spot due to being outside of peripheral vision)

SUMMARY

Advanced Driver Assistance Systems (ADAS) have become commonplace in the automotive industry over the last few decades. Even with the advent of ADAS, however, there are still a significant number of accidents and fatalities. ADAS has in some instances been shown to significantly reduce the number and severity of accidents. Manufacturers are working to avoid ADAS plateauing for effectiveness, which has led the industry to pursue various avenues of investment to ascend the next mountain of challenges – vehicle autonomy, smart mobility, connectivity, and electrification – for reducing accidents and injuries. A number of studies pertaining to ADAS scrutinize a specific ADAS technology for its effectiveness at mitigating accidents and reducing injury severity. A few studies take holistic accounts of ADAS. There are a number of directions ADAS could be further progressed. Industry manufacturers are improving existing ADAS technologies through multiple avenues of technology advancement. A number of ADAS systems have already been improved from passive, alert or warning, systems to active systems which provide early warning and if no action is taken will control the vehicle to avoid a collision or reduce the impact of the collision. Studies about the individual ADAS technologies have found significant improvement for reduction in collisions, but when evaluating the actual vehicles driving the performance of ADAS has been fairly constant since 2015. At the same time, industry is looking at networking vehicle ADAS with fixed infrastructure or with other vehicles' ADAS. The present literature surrounding connected ADAS be it with fixed systems or other vehicles with ADAS focuses on the why and the how information is

passed between vehicles. The ultimate goal of ADAS and connected ADAS is the development of autonomous vehicles.

Biologically inspired systems provide an intriguing avenue for examination by applying self-organization found in biological communities to connecting ADAS among vehicles and fixed systems. Biological systems developed over millions of years to become highly organized and efficient. Biological inspiration has been used with much success in several engineering and science disciplines to optimize processes and designs. Applying movement patterns found in nature to automotive transportation is a rational progression.

This work strategizes how to further the effectiveness of ADAS through the connection of ADAS with supporting assets both fixed systems and other vehicles with ADAS based on biological inspiration. The connection priorities will be refined by the relative positioning of the assets interacting with a particular vehicle's ADAS. Then based on the relative positioning data distribution among systems will be stratified based on level of relevance. This will reduce the processing time for incorporating the external data into the ADAS actions.

This dissertation contributes to the present understanding of ADAS effectiveness in real-world situations and set forth a method for how to optimally connect local ADAS vehicles following from biological inspiration. Also, there will be a better understanding of how ADAS reduces accidents and injury severity. The method for how to structure an ADAS network will provide a framework for auto-manufacturers for the development of their proprietary networked ADAS. This method will lead to a new horizon for reducing accidents and injury severity through the design of connecting ADAS equipped vehicles.

CHAPTER 1. INTRODUCTION

1.1 Motivation

1.1.1 Health

In 2018 the World Health Organization (WHO) published that 1.35 million people worldwide had died in road accidents in 2016, which is an increase from 1.15 million people who died in 2000 (Organization 2018). The trend of fatalities has been reported consistently by the WHO which in 2004 estimated that nearly 1.2 million people are fatally injured in automotive accidents with another 50 million receiving lesser injuries (Murray, Lopez et al. 2001, Peden, Scurfield et al. 2004). At that time, 2004, the WHO believed that those values could rise by up to 65% between 2000 and 2020 (Kopits , Murray, Lopez et al. 1996). While the rate of death in that time per 100,000 has decreased from 18.8 to 18.2, there exists a disparity between low-income countries, where the average per 100,000 is 27.5, and high-income countries, where the average per 100,000 is 8.3 (Organization 2018). Human error is thought to be the reason for 90% of all automotive accidents by the WHO, which has set the removal of human error as a priority (Peden, Scurfield et al. 2004).

1.1.2 Full-Size Light-Duty Pickup Trucks (FSLDPTs)

Each year, over 30,000 Americans are killed in motor vehicle accidents and approximately a third of those accidents involve FSLDPTs with a Gross Vehicle Weight (GVW) of 5,000 to 10,000 lbs. (NHTSA 2010, NHTSA 2011, NHTSA 2012, NHTSA 2013, NHTSA 2014, Mosquet, Andersen et al. 2015, NHTSA 2015, NHTSA 2016, NHTSA 2017, NHTSA 2018). Trucks make up approximately 56% of all registered vehicles in the United States (Administration 2019) with FSLDPT comprising 18% (Company 2020). This is a significant percentage of the vehicle population in the United States, which has been neglected to be studied. FSLDPTs are larger, less maneuverable, and they tend to have larger blind spots than sedans (ConsumerReports 2014). When it pertains to trucks, studies favor evaluating heavy/freight trucks because of their commerce usage. Freight Trucks have been using ADAS since the 90s (Kunze, Haberstroh et al. 2011); whereas, FSLDPTs have only recently adopted ADAS in the last decade. Due to the size, weight, and towing differences between pickup trucks and freight trucks studies about the safety and effectiveness of ADAS in freight trucks cannot be translated to pickup trucks (Jones 2019). For the United States, the significant percentage FSLDPT represent of registered vehicles signifies a critical component of the US transportation network that has been neglected in terms of evaluation of ADAS performance.

1.1.3 Financial

With the push to remove/reduce human error in driving, there is arguably only so much that consumers are willing to pay for an uncertain amount of increased vehicle safety. In a study conducted by the Boston Consulting Group in 2015, the cost of all ADAS features was greater than the consumer's willingness to pay for the features (Mosquet, Andersen et al. 2015). For Adaptive Cruise Control, Forward Collision Warning, and Front Sensors the disparity was over $1000 (Mosquet, Andersen et al. 2015). Since the time of the Boston Consulting Group's study, ADAS have been improved to a level that is marketed as being able to provide a high degree of safety with a reduction to the upfront cost to the consumer. The future fatalities projected by the WHO back in 2004 may have been curbed due to the greater availability of ADAS equipped vehicles in high-income countries. This would potentially explain the disparity in rate of death per 100,000 between high- and low-income countries. In order for the rates to be more equitable, the economics of ADAS must be considered if any real improvement to safety in the real-world is to be achieved.

1.1.4 Industry

Research into ADAS has been conducted for over two decades in various aspects. This research can be divided among a few areas of interest – insurance, component, consumer response, and platooning/networking. Studies concerning insurance look at how a technology, set of technologies, driver actions/characteristics, or environmental factors affect driver safety (Williams 1985, Meng, Wevers et al. 2004, Braitman, McCartt et al. 2010, Neelima Chakrabartya 2013, Eichelberger and McCartt 2014, Li, Werber et al. 2014, Administration 2015, Blincoe, Miller et al. 2015, Cicchino and McCartt 2015, Fildes, Keall et al. 2015, Eichelberger and McCartt 2016, Institute 2016, Isaksson-Hellman and Lindman 2016, Cicchino 2017, Cicchino 2017, Cicchino and Zuby 2017, Jermakian, Bao et al. 2017, Sternlund, Strandroth et al. 2017, Association 2018, Cicchino 2018, Cicchino 2018, Institute 2018, Reagan, Cicchino et al. 2018, Yue, Abdel-Aty et al. 2018, Cicchino 2019, Cicchino 2019, Institute 2019, Insurance Institute for Highway Safety 2019, Insurance Institute for Highway Safety 2019, Kidd and Reagan 2019, NHTSA 2019, National Safety Council 2020). A large portion of these studies were conducted by researchers for the Insurance Institute for Highway Safety (IIHS), which focused predominately on individual technologies and suits of technologies. These studies crossover with component studies which look at the effectiveness of a technology or suite of technologies, but component research also includes development and improvement of the technology or suite of technologies (Fildes, Keall et al. 2015, Eichelberger and McCartt 2016, Isaksson-Hellman and Lindman 2016, Cicchino 2017, Cicchino 2017, Sternlund, Strandroth et al. 2017, Cicchino 2018, Cicchino 2018, Kukkala, Tunnell et al. 2018, Cicchino 2019, Cicchino 2019, Kidd and Reagan 2019). The third category of ADAS research is consumer response, which looks at aspects of willingness to pay and technology acceptance (Molin and Marchau 2004, ConsumerReports 2014, Mosquet, Andersen et al. 2015, Choi, Thalmayr et al. 2016, Mosquet, Andersen et al. 2016, Reagan, Cicchino et al. 2018, Daniel Holland-Letz 2019, Beiker and Burgelman 2020, Maike Schlumbohm 2020, Preston 2020). These studies include research by consulting firms such as the Boston Consulting Group, and their findings are used by manufacturers as guidance for increasing consumer acceptance of ADAS. Studies on platooning and networking of ADAS vehicles have largely looked at simulations and limited vehicle tests (Nadeem, Dashtinezhad et al. 2004, Yang, Liu et al. 2004, Kunze, Haberstroh et al. 2011, Hafner, Cunningham et al. 2013, Sun, Tang et al. 2017, Yuan, Tasik et al. 2020).

The research builds on all four of the aforementioned areas of interest and incorporates self-organization that are founded on biologically inspired rules pertaining to movement behavior.

1.2 Research Questions and Goals

This section introduces the overall research question and outlines research goals and fundamental contributions that will result from answering this question.

1.2.1 Overall Research Question (RQ)

Does biological inspiration, in the form of communication pertaining to movement behavior, for the design of connected ADAS lead to an improvement of ADAS as measured by reductions in costs – upfront and post-accident – and improved performance – reduction of accidents and injury severity.

1.2.2 Research Goals (RGs)

RG1. Quantitatively determine the statistical significance of ADAS at reducing injury severity and identify key factors that contribute to the performance of the ADAS technology derived from the National Highway Traffic Safety Administration (NHTSA) Fatality Analysis Reporting System (FARS) database.

RG2. Determine what regions/zones of the vehicle should be identified as possessing room for improvement based on heuristics of accidents and financial considerations regarding upfront and post-accident expenditures.

RG3. Identify biological communication for movement to address the performance gaps identified in RG2, diminishing the incidence of these regions being collide with to better align with the other regions of the vehicle.

RG4. Postulate the projected performance improvement and costing along the two branches – continued refinement of existing ADAS and development of V2X ADAS interface – being pursued by industry for enhancing ADAS.

1.3 Contributions and Significance

This dissertation advances the work being done in ADAS technology development through modeling and simulation grounded in quantified real-world data. Even though limited real-world data has been used to in models and simulations of motor vehicle accidents, the incorporation of biologically inspired self-organization for cohort movement has not been proposed or evaluated for efficacy of mitigating automotive accidents and injuries.

The anticipated outcomes of this research are:

(i) A biologically inspired connected vehicle model validated through simulations that combines the human engineered system and biological solutions. The biologically inspired model would provide guidance for the connection of vehicles which is suitable for the industrial sector to develop derivatives for V2X networks. This novel approach would orient manufacturers for the development of the next generation of ADAS technologies.

(ii) The first study the effectiveness of ADAS in FSLDPTs. This would provide insight to a large percentage (18%) of registered vehicles on the roads in the United States that has been neglected in past studies of ADAS because of its exclusivity of being neither a sedan nor a freight truck. Stochastic and heuristic findings of FSLDPTs would benefit governments at both the municipal and federal levels for drafting and enacting transportation laws.

(iii) A dissemination of which ADAS technologies were effective at reducing accidents and reducing the severity of injuries contrasted to those which exist for driver convenience. This translates to auto-manufacturers being able to stratify which technologies are worth continued improvement, which are satisfactory as is, or which could be depreciated while still providing the same level of aptitude. Currently, there is research and investments being made in every aspect of ADAS technologies. This contribution would inform the research community where to focus their efforts to provide the largest return on investment.

(iv) An insight into the economics of ADAS regarding costing and pricing. By evaluating the cost to the consumer for the level of additional safety provided by ADAS technologies offered by a particular auto-manufacturer relative to other auto-manufacturers, the consumer would be better equipped to make a conscientious decision when purchasing a vehicle. Auto-manufacturers would gain knowledge of how much to invest to see improvement in vehicle safety.

1.4 Research Plan

The research question (RQ) and goals (RGs) are answered by completing the following research tasks (RT).

1.4.1 Research Tasks (RT)

RT1. Collect real-world accident data with thorough literature reviews, data mining, financial reports, and internet searches.

RT2. Collect information on biological principles of self-organization for comparison, with thorough literature reviews and internet searches.

RT3. Analyze the datasets of real-world data using heuristics and stochastic analysis with a focus on FSLDPTs.

- **a.** Compare the heuristics for the FSLDPTs among all seven automobile manufacturers.
- **b.** Breakout the FSLDPTs with ADAS from the rest of the FSLDPTs.
  - i. Identify a common grouping for FSLDPTs with ADAS for a relative comparison among the brands.
  - ii. Identify factor(s) that can be used to assess the performance of ADAS.
- **c.** Perform stochastic analysis to determine statistical significance of FSLDPT with ADAS performance.
- **d.** Perform stochastic analysis to determine contributing factors statistical significance of FSLDPT with ADAS performance.

RT4. Analyze the economic metrics associated with cost of an accident.

- **a.** Optimize impact location selection using repair cost, injury cost, and injury severity for determination of best and worst vehicle locations to be impacted.

RT5. Investigate whether it is better for automobile manufacturers to continue the present trajectory of ADAS development or explore V2V based on biological inspiration.

- **a.** Use existing accident data to develop a model for future accidents based on current trends in accident/injury reduction.
- **b.** Using biological inspired self-organization as a benchmark to develop a model for vehicles using present ADAS accident data in a V2V setup.

1.4.2 Detailed Work Plan

RT1: A detailed and exhaustive set of accident automotive data is a vital component for this research. There exist multiple avenues for ascertaining this data following a thorough literature reviews, data mining, financial reporting, and internet searches. Literature includes (but not limited to) consumer reports, government reports, traffic journals, accident journals, consulting firm reports, insurance reports, and technical journals. Data mining is available through insurance agencies, NHTSA, IIHS, state government accident reports. Financial reporting will be obtained through SEC annual reports such as company 10-K and 20-F reports. Internet searches include (but not limited to) sales brochures and traffic safety factsheets. As for obtaining real-world complete and detailed accident data there exists no such data set. Partial sets are available through insurance agencies; however, these are proprietary data sets and due to privacy laws are next to impossible to obtain. Each state produces limited detailed fatal accident reports that are inconsistent from state to state making unification of these independent incongruent datasets unrealistic. By limiting the real-world data to a complete and detailed set of accidents resulting in one or more fatalities, a useful and detailed data set is obtainable from NHTSA known as FARS. NHTSA also produces a speculative dataset that generalizes non-fatal accidents known as the Crash Report Sampling System (CRSS). The NHTSA FARS data can be organized and sorted be queried and analyzed in RT3.

RT2: Self organized movement in aggregations of organisms (i.e. swarms, flocks, schools) is a common occurrence in nature. A thorough literature review of academic journals was conducted. The patterns and trends from literature will be combined with the data analyzed from RT3 to construct a model for RT5's biologically inspired V2V (vehicle-to-vehicle) self-organization. While there are V2V models that have been developed, none of those models have looked at incorporating biologically inspired patterns for self-organization of cohort movement. Some existing research for V2X (vehicle-to-infrastructure/vehicle) points out the limitations of data transfer between sender and receiver (Nadeem, Dashtinezhad et al. 2004). Other research in V2X deals with how the vehicles interact to avoid accidents based on how the research perceives a system should work (Yang, Liu et al. 2004, Kunze, Haberstroh et al. 2011, Hafner, Cunningham et al. 2013, Yuan, Tasik et al. 2020). This work will use biological inspiration for the methodology of how V2V should interact, which has not been applied previously by other researchers.

RT3: The data assembled (NHTSA FARS) and organized as part of RT1 is filtered for the seven FSLDPTs. The data is then graphed to visualize the factors in the dataset. From the factors identify those that can be used to compare the accidents (Level of Injury and Damage Severity). Comparing the two factors identified for comparing accidents to select one factor (Level of Injury) to use for all comparisons. The seven brands of FSLDPTs are normalized by dividing the total accidents by the number of units sold in the corresponding year found using financial reports and internet searches. Then FSLDPT brands can be compared now they are normalized using the factors from the dataset. The FSLDPTs equipped with ADAS will then be broken out using identifying factors from the dataset. Should factors such as VIN not be complete, for protecting personal identifiable information, other factors to stratify FSLDPTs with ADAS and those without ADAS will be identified through the means of association of other factors. These other factors can be identified through the use of sales brochures. Now with ADAS FSLDPTs identified, stochastic analysis such as ANOVA tests to identify factors that influence the performance of ADAS FSLDPTs. The ANOVA test (analysis of variance test) is a stochastic tool that compares the variances of two or more groups of data. The ANOVA test determines if the datasets are in fact the same datasets or different distinct sets of data. If there is no real difference between the datasets, the null hypothesis, the result of the ANOVA P-value (or F-ratio) will be near 1, and if there is a significant difference between the datasets, the result of the ANOVA P-value will be less than 0.05. By convention, statistical significance is set as a P-value less than 0.05, which indicates there is a less than a 5% probability that the two datasets are from the same population. In this research a single factor ANOVA is used with the independent variable used in the test is the Level of Injury. The one-way

ANOVA is selected over the two-way ANOVA due to the other possible variable for comparison (Damage Severity) not being independent of Level of Injury. From the factors identified as being significant contributors to the performance of ADAS, they are then tested using the ANCOVA test to identify any covariables that in combination would contribute to the performance of ADAS. ANCOVA is similar to ANOVA but accounts for additional continuous ordinal variables for determining grouping of data significance.

RT4: The only way automotive manufacturers will change how they are deploying ADAS technology is if market forces shift their interests. Economics of accidents is one of such market forces that can have that effect. Using economic and accident data obtained in RT1 to create a model that can be optimized to indicate where the most expensive and severe impacts occur for an accident will be used to justify future deployment needs and designs of ADAS technologies. It also will help distinguish between ADAS for safety and ADAS for convenience. By using a single dataset for pricing of components (Automotive 2019), even if the quoted values for the components is inaccurate the relativism of the pricing used in the model will be consistent. The results from the optimization support RT5a for reasoning on what needs continued improvement and investment and RT5b for what issue doe the biological inspiration need to address most predominately.

RT5: Comparing the two directions (current ADAS and Bio-inspired ADAS) that could be taken for the next stage of ADAS development is a quantitative method for deciding the best investments for automotive manufacturers and researchers. RT5a is a regression analysis based on the trends in investment, pricing, accident occurrence, and injury severity. The regression analysis will then be projected forward to predict what can be expected from the continued course of ADAS development. RT5b involves developing a model for CV using patterns of biologically inspired self-organized cohort movement. The patterns from fish and birds will be a strong influence on the model as these two classes of animals behave similarly for self-organization for cohort movement. They will also be used to examine the information passed between the CVs and for recognizing which vehicles should communicate. These two tasks' resultant models will then be compared for accident occurrence, injury severity, and associated costs for each model.

1.5 Assumptions

This research makes two assumptions regarding the data used for the construction of models. The first assumption stems from the use of NHTSA's FARS dataset, which only includes accidents where someone involved in the accident perished. Here it is assumed that the behavior of the vehicle mechanics is similar enough to those involved in non-fatal accidents that findings from the FARS dataset can be interpolated to non-fatal accidents. With data regarding non-fatal accidents not being as consistently detailed and comprehensive, the FARS dataset from NHTSA is the best source for real-world data regarding accidents.

The second limitation made by this research is that FSLDPTs, which comprise about 20% of the vehicles on the road, are suitable agents to evaluate the effectiveness of ADAS. Models built using the trends found from evaluating FSLDPT accident data are commutable to the general population of vehicles. Inevitably, there will be some differences in the behavior of different vehicle makes and models. The methodologies proposed in this research could be applied to a more extensive body of data regarding ADAS effectiveness, but the prospect of substantial differences in outcomes is unlikely.

1.6 Dissertation Layout

This dissertation covers a range of aspects regarding the development of ADAS from currently deployed systems on Full-Size Light-Duty Pickup Trucks (FSLDPTs) to biological inspirations for possible future generations of ADAS. Following this introduction, a thorough literature review covers biological principles that could be applied to vehicle safety. Topics covered are progression of vehicle safety, biological self-organization, biological communication, current state of swarm robotics, a look at the economics of the automotive industry. Highlighted in the review is the largest gap in evaluating the effectiveness of ADAS that is the FSLDPT.

Chapter 3 then evaluates the process of driving through the use of functional decompositions and flow diagrams. The actions done during driving to avoid being in a crash are functionally decomposed and areas for possible improvement from biological principles are identified. This process is then inversed to look at how a vehicle gets into a crash as a way to ensure all relevant topics are covered.

Next, Chapter 4 analyzes the current effectiveness of ADAS in FSLDPTs. It partitions the evaluations of ADAS into factors of interest, the seven different main FSLDPT models, how ADAS performs during adverse conditions, and the economics of ADAS. These findings are then incorporated into the simulations of Chapter 5. There the data analyzed in Chapter 4 is used to find optimized positioning of ADAS as well as discuss the environmental sustainability of ADAS. The chapter is rounded out by proposing what future ADAS design will be improved based on following of its present design trajectory.

Chapter 6 then breaks into what a new path for ADAS could be using principles pulled from biological systems. This reaches back to the biological findings from Chapter 2 and applies them to vehicle safety. A path is proposed based on all the findings and then evaluated in Chapter 7. In Chapter 7, both analytical analysis and optimizations are used to determine if a biologically inspired connected ADAS (BICADAS) could prevent crashes. The results are then compared to a human driver's performance under the same conditions, and then BICADAS is compared to ADAS in Chapter 8. The comparison is done on the grounds of crash prevention, technology costs, and other sustainability benefits.

1.7 Summary

Does biological inspiration, in the form of communication pertaining to movement behavior, for the design of connected ADAS lead to an improvement of ADAS as measured by reductions in costs – upfront and post-accident – and improved performance – reduction of accidents and injury severity? This proposed research question by this work, developed with the goal of reducing automotive crashes. The overall goal and question are answered through the completion of a series of tasks outline that examine the utility of biological principles and how they may be applied to vehicle safety. The completion of these tasks result in a set of primary and secondary research contributions that significantly influence the success for designing biologically inspired connected advanced driver assistance systems (BICADAS). The primary contributions of this dissertation are:

1. A biologically inspired connected vehicle model validated through simulations that combines the human engineered system and biological solutions.
2. The first study the effectiveness of ADAS in FSLDPTs.
3. A dissemination of which ADAS technologies were effective at reducing accidents and reducing the severity of injuries contrasted to those which exist for driver convenience.
4. An insight into the economics of ADAS regarding costing and pricing.

A number of secondary contributions to the BICADAS were also formulated during the completion of this dissertation. The subsequent chapters detail the range of this work, from a literature review through the development of BICADAS and the comparison of BICADAS to present ADAS. This work concludes with the proposal of several ideas for future work and improvements to be advanced in this field.

CHAPTER 2. LITERATURE REVIEW

2.1 The Progression of Vehicle Safety Development

The automotive industry has a long history of implementing safety features in automobiles going as far back as the 1880s with the introduction of headlamps. Since then, automotive safety advancements have been a gradual over the nearly 150 years. The timeline of the development of safety features is depicted in Figure 1 which is based on the timelines for safety technology by the Boston Consulting Group (Mosquet, Andersen et al. 2015, Mosquet, Andersen et al. 2016).

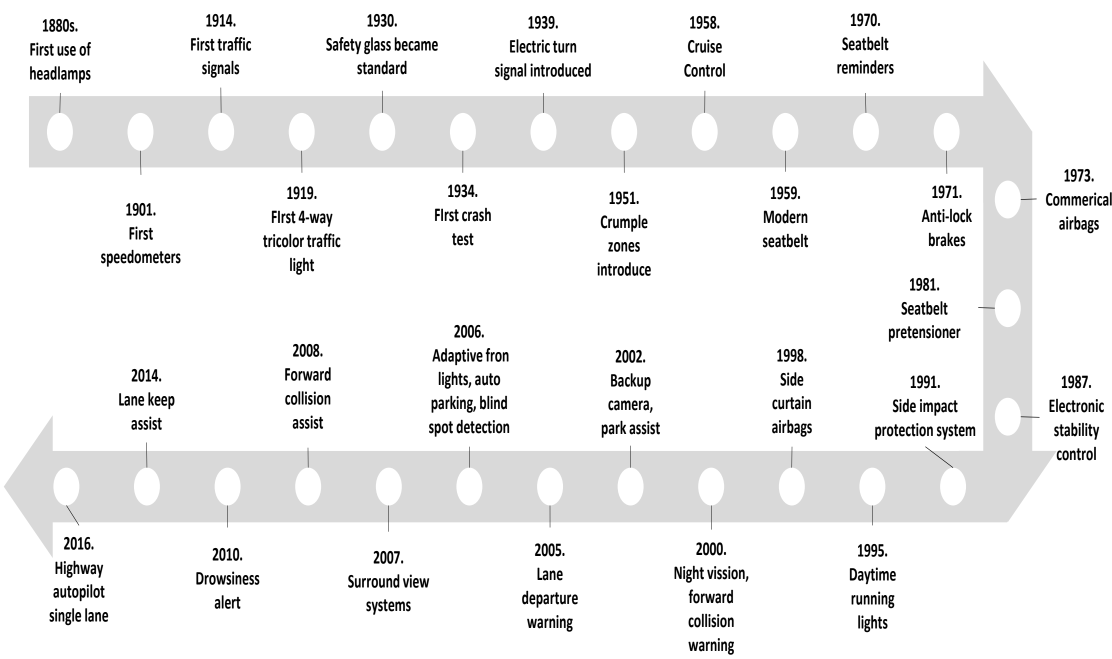

Figure 1. Timeline of safety feature development.

While most of the technologies in Figure 1 were developed to improve the safety of the vehicle occupants, not all of these technologies actually improve safety. A good number of them, are better understood as features that provide a convenience to the driver by increasing comfort and efficiency (Lin, Ji et al. 2018). Features that do improve safety can be divided into two interlaced groups:

- Those likely to prevent serious accidents, where the possibility of occupant injury or death is high, and
- Those likely to prevent cosmetic damage to the vehicle.

The turn of the 21st century is viewed as the advent of intelligent vehicles with the 2010s giving rise to low level autonomy. At the beginning of the 2000s the WHO published their concern that automotive fatalities worldwide could rise by 65% from 1.2M in 2004 to 2M by the year 2020 (Kopits , Murray, Lopez et al. 1996). Around this time ADAS was introduced to the consumer automotive market. While causation is difficult to prove the increase in fatalities by 2020 only reached 1.35M a 12.5% increase in fatalities. When broken down further between high-income versus low-income countries, the increase in fatalities is driven predominately by low-income countries. ADAS equipped vehicles cost more than their non-ADAS counterparts, and it is permissible that the lesser increase in fatalities for high-income countries than low-income countries can in some part be accredited to ADAS. Of course, there are other factors which play a sizable role in the disparity between surviving a car accident in a high-income country as opposed to a low-income country – healthcare, traffic laws, and accessibility to accident location to name a few.

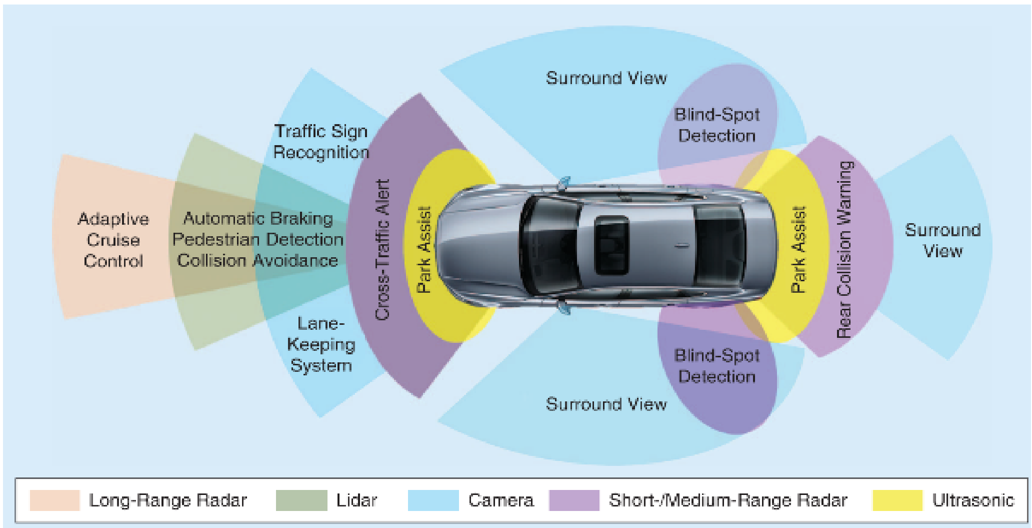

Figure 2. Visualization of ADAS technology (Kukkala, Tunnell et al. 2018).

Vehicle autonomy has six levels from 0-5 for which the level of control ADAS has over the driving of the vehicle creates the stratification. Level 0 has no automation and is entirely human controlled (KBB 2020, Synopsys 2021). Level 1 automation provides warning for impending danger to the human driver and can take action in one direction (i.e. speed up/slow down), while level 2 is the automation taking the corrective action for the driver in two directions – speed up/slow down/change lanes (KBB 2020, Synopsys 2021). Level 3 is where the vehicle using ADAS and GPS under stringent conditions for the road, such as physical barriers for segregation, perform driving tasks, but the driver is ready to take over control when needed (KBB 2020, Synopsys 2021). Level 4 is when having a human driver is unnecessary and the vehicle controls all aspects of driving on all roads, and it is only limited in that it requires speed limits and geofencing software for an area

(KBB 2020, Synopsys 2021). Level 5 is full autonomy with no driver with no geographical or speed limitations, and it could potentially work off V2X communications with ADAS for obstacle avoidance (KBB 2020, Synopsys 2021).

Table 1: ADAS features with functions and sensors utilized.

ADAS Feature	Abbreviation	Function
Adaptive Cruise Control	ACC	Cruise control with the added ability to use the FS to also maintain a set distance from a leading vehicle.
Adaptive Cruise Control with Stop and Go	ACCSG	ACC that has the added ability to brake as needed and start moving again with traffic.
Adaptive LED Headlamps	ALED	Based on lighting conditions driving lights adjust for light exposure changes.
Automatic High Beams	AHB	Detects other vehicles and adjusts between high-beams and low beams.
Blind Spot Warning	BSW	Using sensors to detect obstacles next to the vehicle and provide the driver with an alert warning.
Forward Collision Warning	FCW	Through the use of FS for detection of objects approaching the front of the vehicle and provide the driver with an alert warning.
Forward Collision Warning with Brake Support	FAEB	Using the FS applies brakes should the driver's response time not be sufficient to prevent a crash.
Forward Sensing	FS	The combined use of radar and cameras on the front of the vehicle.
Hill Descent Control	HDC	Using traction control and anti-lock brakes to prevent slipping down steep hills.
Hill Start Assist	HSA	Maintains brake pressure until the engine produces enough torque to move vehicle uphill.
Lane Departure Warning	LDW	Using side cameras to determine if the vehicle is drifting out of its lane without a turn signal.
Lane Keeping	LK	Using the LDW system to steer the vehicle back into the center of the lane should the driver's response time not be sufficient to stay in lane.
Park Assist	PA	Using radar and ultra-sonics to detect objects that impinge the vehicles parking path.
Rear Cross-Traffic Alert	RCTA	Using BSW sensors to detect during backing up to alert the driver should another vehicle approach.
Rear Sensing	RS	The combined use of radar and cameras on the rear of the vehicle.
Rear View Cameras	RVC	Rear facing camera which provides the driver with a clear view of what is behind the vehicle.
Surround View Cameras	SVC	Stitching together of vehicle cameras to create a 360-degree view of around the vehicle.

ADAS technology has not been stagnant since its introduction in the 2000s. The early versions of ADAS have been improved and even transformed. Early ADAS technologies played passive roles simply alerting the driver to potential danger. Newer

ADAS technologies took the early warning of older ADAS technologies and added the ability for the vehicle to self-correct when the driver's response was not quick enough (Kukkala, Tunnell et al. 2018). For example, older ADAS, lane departure warning, would warn the driver if it determined they were drifting out of their lane, while newer ADAS, lane keep assist, will first alert the driver and then steer the vehicle back to the center of the lane.

Different auto-manufacturers offer competing packages and bundles each of which combine various ADAS technologies. Table 1 list and describes the individual ADAS technologies common at the time of this dissertation. It should be noted that for marketing purposes different auto-manufacturers will brand their variation of each ADAS technology differently. Case in point, Ford has their Blind Spot Information System (BLIS), while Toyota has their Blind Spot Monitoring (BSM). Both systems perform the same function, which is to alert the driver of an object outside the driver's visible spaces. Differences between the ADAS by automotive brand is discussed in (Fish and Bras 2021). As for year over year for each technology there is only minor improvement except when a new technology is introduced. Figure 2, which is from the system coverage figure found in (Kukkala, Tunnell et al. 2018), maps the regions each of the individual ADAS technologies is responsible for monitoring. When discussing ADAS usage, it is important to remember that machine intelligence and human intelligence are complementary, and their combined usage of machine computing power and human interpretation working in unison determine the effectiveness of ADAS (Huang, Chen et al. 2020).

2.2 Self-Organization for Cohort Movement Found in Biological Systems

Biological inspirations have been used in multiple varying forms of engineering (Kar 2016). The thinking is that organisms and systems that occur in nature have spent millennia evolving and optimizing to best serve their needs for survival (Kar 2016, Tee Qiao Ying 2018). Many prominent algorithms used for optimization have biological roots such as neural networks (Cao and Jun 2003, Yu and Cao 2006, Miramontes, Melin et al. 2020), ant colony (Blum 2005, Dorigo and Blum 2005), and particle swarm (Sun, Feng et al. 2004, Das, Abraham et al. 2008, Miramontes, Melin et al. 2020) to reference a few. A thorough breakdown of the different biologically inspired algorithms and their applications is provided in (Kar 2016).

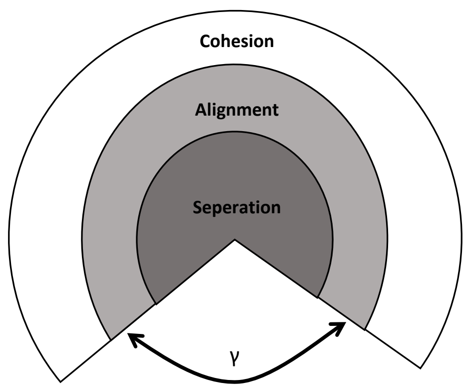

Figure 3. Areas of separation, alignment, cohesion including dead angle (γ) based on

Different animal species travel in aggregates over different spans of distance. Some examples of cohort movement are seen in schools of fish, swarms of bees, colonies of ants, and flocks of birds. These groups of animals have been studied and compared for how they organize movement within the aggregations. Fish and birds in particular have similar models, with a few exceptions (Reynolds 1987, Couzin, Krause et al. 2002, Inada and Kawachi 2002, Hemelrijk and Hildenbrandt 2012). Organizational structure of these cohorts can be influenced by four characteristics: mechanics of locomotion, local interactions, environmental contributions, and perception of surroundings (Hemelrijk and Hildenbrandt 2012). The mechanics of locomotion is physics dependent for how movement occurs. In the cases of fish and birds, fluid dynamics contributes to the similarity between birds and fish. Local interactions pertain to how the individual communicates with the nearby individuals in the aggregation. Some theories about how birds decide to turn involve voting through the means of turning slightly toward the flock's interior momentarily, as is the case with dunlin (*Calidris alpine*) (Heppner and Grenander 1990). Environmental contributions refer to factors pertaining to weather and homing (e.g. tendency towards roosting area) that set the overall goal or direction of movement. Perception of surroundings refers to the individual's observation of those around them. Figure 3 based on (Hemelrijk and Hildenbrandt 2012) shows how perception is used for spacing influenced by neighbors. Based on perception individuals can self-organize and adjust their velocities by either speeding up or slowing down to form better cohesion with the cohort (Hemelrijk and Hildenbrandt 2012). Individuals are better equipped to slow down to avoid collisions with fellow cohort members rather than speeding up because of the individual's inability to detect members occupying space outside of their peripheral vision referenced by Hemelrijk and Hildenbrandt as the dead angle (γ) (Hemelrijk and Hildenbrandt 2012).

2.3 Biological Communication and Sensing for Navigation

Communication and Sensory perception in biology are sizable contributors to animal navigation especially in the cases of communal animals (i.e., ants, birds, fish, etc.). There are many reasons for animals to communicate from food scavenging to predator avoidance to migration. A good portion of what is being communicated about is based on sensory perception.

There are four main means that signals are readily detected – auditory, haptic, olfactory, and visually detected (Eftimie, De Vries et al. 2007). Of these four, olfactory – the sense of odor – is the least applicable to the application of this research (automotive collision mitigation). This is due to odor diffusion and dissipation makes it hard to analyze smells especially for directionality (Bossert and Wilson 1963). While pheromones are used by many animals for navigation and communication, it is not the preferred manner to communicate navigation as seen in ant navigation (Garnier, Combe et al. 2013).

Ants will use visual information to orient themselves and navigate (Garnier, Combe et al. 2013). Some ant species will use celestial navigation (Wehner and Menzel 1969, Menzel, Kirbach et al. 2011) while others will navigate using the canopy of a forest (Hölldobler 1980) and others rely on their memory of landmarks on their travels (Chameron, Schatz et al. 1998, Menzel, Kirbach et al. 2011). Biological signaling can be communicated through color displays which an animal may display such as warning and sexual attraction. For personal protection animals will perform aposematism – visual anti-predator signaling to the predator of a warning that attack will likely precipitate negative outcomes for the aggressor (Caro and Allen 2017). This principle could potentially be applied to current ADAS equipped vehicles using the sensors in the rear of the vehicle to illuminate brake lights when vehicles approaching from the rear get to close for safe following, further discussion on this topic found in Chapter 6.

Visual signal processing does possess limitations. Leuckart's law states that there is a direct relationship between the size of the animal's eye and how fast they can travel (Leuckart 1876). Further investigation has found that the mass of the animal is also interrelated to eye size and maximum running speed (Heard-Booth and Kirk 2012). Visual processing can also be misleading to animals. The closer animals are to a surface or the faster it moves the greater the rate of optic flow is perceived by the animal (Scholtyssek, Dacke et al. 2014). The perceived increase in the optic flow rate causes most animals to slowdown such as bees (Scholtyssek, Dacke et al. 2014). Interestingly, fish do not utilize optic flow for determining velocity because unlike bees and birds they are able to mitigate the effects of acceleration due to their buoyant nature being in water allows them to stop with little deceleration (Scholtyssek, Dacke et al. 2014). Still animals such as cod (*gadus morhua*) and herrings (*clupea harengus*) rely on visual sensing to maintain distance among neighbors. For flocks coordinated near instantaneous movement can be accomplished by allelomimetic behavior – where each individual reacts in response to their neighbors (Fetecau and Guo 2012). It is though this behavior that animals in flocks rely for spacing with other animals in the blind zone/ dead angle (Fetecau and Guo 2012). This plays in with collision avoidance being dependent on visual ques but for close spacing in some animals haptic sensing such as insects using antennae are more heavily relied upon (Baba, Tsukada et al. 2010, Chan and Gabbiani 2013, Benaragama and Gray 2014, Romey, Miller et al. 2014). The haptic sensing is not applicable to this research as the purpose is to prevent collisions among vehicles.

Unlike haptic sensing acoustic sensing is already being utilized in vehicles for vehicle spacing. Social bees and hornets utilize acoustic signals to construct highly organized and precise hives using ultrasonic waves to determine spacing of the honeycomb structures (Bergman and Ishay 2007). Bats, who rely on echolocation for navigation, are able to distinguish other specific bats based on the uniqueness of the individual's calls (Yovel, Melcon et al. 2009). This is interesting to the topic of vehicle connectivity as the acoustic signals utilized among vehicles for sensing could potentially be unique to each of the vehicle EPA classes or vehicle body types.

Communication among individual animals is critical for group cohesion and self-organization (Eftimie, De Vries et al. 2007). In group social settings, animals must balance what is good for them and what is good for the group such as meerkats turning over food to the dominate members of the group (West, Griffin et al. 2007). This is not far from the bargaining problem first explored by Nash for determining optimal group outcomes for all parties involved (Nash 1950). Dolphins, whose whistle is unique much like how each bat's call is unique, are highly social animals that will join in vocally onto shared calls with other dolphins (King, Friedman et al. 2018). These shared calls will be used to signal proximity to the social group (King, Friedman et al. 2018). Observational and experimental research of wild animals has indicated that animal vocalizations do have the potential for specific meanings such as the identification of specific predator types or the location of food sources (Suzuki, Wheatcroft et al. 2020). Interestingly, few animals are able to have their eyes follow another's gaze or point to an object with domestic canine being a notable exception (Byrne 2003). This is why most of the literature regarding visual communication pertains to orientation to another object/animal or coloring/patterning for the transmission of signals. The lack of specificity in these communication methods leads to interpretation errors in the communication (Lee, Ward et al. 2017). In turn the recipient of the signal often takes the safest action based on their interpretation of the signal (Lee, Ward et al. 2017). Signal interpretation and error mitigation will be an important aspect of any setup for connected vehicles, and biology would suggest taking the safest course of action and then transitioning to a better course of action should produce the most favorable outcomes.

2.4 Swarm Robotics

Swarm robotics, while it may seem to be relevant to this research on biologically inspired connected vehicles, is to simplified and constrained at its current development state to be useful for the complexity of vehicle connectivity. The review of swarm robotics was conducted using the Web of Science Core Collection. In the aforementioned database the term “swarm robotics” was queried. The resulting references were then limited to those that had been cited twenty or more times by other peer reviewed journal articles. Many authors define swarm robotics as a large group of robots organized in a display of collectively intelligent behavior to achieve an objective that would be outside the competencies of a solitary robot (Beni 2005, Garnier, Gautrais et al. 2009, Campo, Gutiérrez et al. 2010, Arvin, Samsudin et al. 2011, Pini, Brutschy et al. 2011, Barca and Sekercioglu 2013, Pimenta, Pereira et al. 2013, Bandala, Dadios et al. 2014, Ducatelle, Di Caro et al. 2014, Francesca, Brambilla et al. 2014, Castello, Yamamoto et al. 2016, Duarte, Costa et al. 2016, Francesca and Birattari 2016, Kolling, Walker et al. 2016, Scheidler, Brutschy et al. 2016, Schranz, Umlauft et al. 2020). The field of swarm robotics lays at the intersection of swarm intelligence and mobile robotics (Dorigo, Trianni et al. 2004, Dorigo, Tuci et al. 2004, Martinoli, Easton et al. 2004, Mondada, Pettinaro et al. 2004, Seyfried, Szymanski et al. 2004, Beni 2005, Dorigo 2005, Sahin 2005, Gross, Bonani et al. 2006, Sharkey 2006, Trianni, Nolfi et al. 2006, Mohan and Ponnambalam 2009, Schmickl, Thenius et al. 2009, Bonani, Longchamp et al. 2010, Campo, Gutiérrez et al. 2010, Tan and Zheng 2013, Bandala, Dadios et al. 2014, Couceiro, Vargas et al. 2014, Duarte, Costa et al. 2016). Much of the development of swarm intelligence stems from biological inspiration from birds, fish, insects, and other biological systems (Kube and Bonabeau

2000, Payton, Estkowski et al. 2003, Payton, Estkowski et al. 2004, Sahin 2005, Balch, Dellaert et al. 2006, Correll, Sempo et al. 2006, Schmickl and Crailsheim 2007, Garnier, Jost et al. 2008, Schmickl and Crailsheim 2008, Christensen, OGrady et al. 2009, Campo, Gutiérrez et al. 2010, Mayet, Roberz et al. 2010, Arvin, Samsudin et al. 2011, Doursat, Sayama et al. 2013, Virágh, Vásárhelyi et al. 2014, Kolling, Walker et al. 2016, Oh, Ramezan Shirazi et al. 2017, Suárez, Iglesias et al. 2019, Connor, Champion et al. 2021). Swarm robotics offer five main advantages:

- Improved performance by parallelization – having robots preforms multiple tasks at once to achieve an end goal (Pinciroli, Trianni et al. 2012, Barca and Sekercioglu 2013, Couceiro, Vargas et al. 2014, Castello, Yamamoto et al. 2016, Senanayake, Senthooran et al. 2016, Suárez, Iglesias et al. 2019),
- Task enablement – having groups of robots preform separate hierarchical tasks to achieve a common goal (Dorigo, Trianni et al. 2004, Seyfried, Szymanski et al. 2004, Gazi and Fidan 2006, Sharkey 2006, Soysal and Şahin 2006, Liu, Winfield et al. 2007, Berman, Halasz et al. 2009, Arvin, Samsudin et al. 2011, Pini, Brutschy et al. 2011, Brambilla, Ferrante et al. 2013, Pimenta, Pereira et al. 2013, Pini, Brutschy et al. 2013, Bandala, Dadios et al. 2014, Brutschy, Pini et al. 2014, Ducatelle, Di Caro et al. 2014, Ferrante, Turgut et al. 2015, Castello, Yamamoto et al. 2016, Duarte, Costa et al. 2016, Scheidler, Brutschy et al. 2016, Castelló Ferrer 2019, Suárez, Iglesias et al. 2019),
- Scalability – using larger numbers of robots to as needed to achieve tasks and maintaining group cohesion (Martinoli, Easton et al. 2004, Spears, Spears et

al. 2004, Sahin 2005, Çelikkanat and Şahin 2010, Liu and Winfield 2010, Arvin, Samsudin et al. 2011, Barca and Sekercioglu 2013, Pimenta, Pereira et al. 2013, Valentini, Hamann et al. 2014, Bayındır 2016, Duarte, Costa et al. 2016, Senanayake, Senthooran et al. 2016, Suárez, Iglesias et al. 2019),

- Distributed sensing and action – ability to have robots sense in one area while another robot acts in a separate area (Dorigo and Şahin 2004, Arvin, Samsudin et al. 2011, Barca and Sekercioglu 2013, Brambilla, Ferrante et al. 2013, Senanayake, Senthooran et al. 2016, Oh, Ramezan Shirazi et al. 2017, Suárez, Iglesias et al. 2019), and
- Fault tolerance – should one robot go offline another is able to act redundantly to take the place of the offline robot (Winfield and Nembrini 2006, Christensen, OGrady et al. 2009, Nouyan, Gross et al. 2009, Duarte, Costa et al. 2016, Oh, Ramezan Shirazi et al. 2017, Suárez, Iglesias et al. 2019).

Most research into swarm robotics occurs through simulation and then a small portion is evaluated using small robots in an enclosed lab environment (Kube and Bonabeau 2000, Payton, Estkowski et al. 2003, Dorigo, Trianni et al. 2004, Dorigo, Tuci et al. 2004, Lerman, Martinoli et al. 2004, Martinoli, Easton et al. 2004, Mondada, Pettinaro et al. 2004, Payton, Estkowski et al. 2004, Seyfried, Szymanski et al. 2004, Spears, Spears et al. 2004, Winfield, Harper et al. 2004, Dorigo 2005, Luke, Cioffi-Revilla et al. 2005, Pugh, Martinoli et al. 2005, Correll, Sempo et al. 2006, Gazi and Fidan 2006, Gross, Bonani et al. 2006, Sharkey 2006, Soysal and Şahin 2006, Trianni, Nolfi et al. 2006, Winfield and Nembrini 2006, Cianci, Raemy et al. 2007, Liu, Winfield et al. 2007, Schmickl and Crailsheim 2007, Garnier, Jost et al. 2008, Schmickl and Crailsheim 2008, Berman, Halasz et al. 2009, Cannon, Hoburg et al. 2009, Christensen, OGrady et al. 2009, Garnier, Gautrais et al. 2009, Gross and Dorigo 2009, Kazadi 2009, Nouyan, Gross et al. 2009, Schmickl, Thenius et al. 2009, Trianni and Nolfi 2009, Bonani, Longchamp et al. 2010, Campo, Gutiérrez et al. 2010, Çelikkanat and Şahin 2010, Liu and Winfield 2010, Mayet, Roberz et al. 2010, Arvin, Samsudin et al. 2011, Montes de Oca, Ferrante et al. 2011, Pini, Brutschy et al. 2011, Sperati, Trianni et al. 2011, Trianni and Nolfi 2011, Ferrante, Turgut et al. 2012, Pinciroli, Trianni et al. 2012, Gomes, Urbano et al. 2013, Marino, Parker et al. 2013, Pimenta, Pereira et al. 2013, Pini, Brutschy et al. 2013, Bandala, Dadios et al. 2014, Brambilla, Brutschy et al. 2014, Brutschy, Pini et al. 2014, Couceiro, Vargas et al. 2014, Ducatelle, Di Caro et al. 2014, Francesca, Brambilla et al. 2014, Krajník, Nitsche et al. 2014, Valentini, Hamann et al. 2014, Virágh, Vásárhelyi et al. 2014, Ferrante, Turgut et al. 2015, Valentini, Hamann et al. 2015, Arvin, Turgut et al. 2016, Castello, Yamamoto et al. 2016, Duarte, Costa et al. 2016, Francesca and Birattari 2016, Scheidler, Brutschy et al. 2016, Senanayake, Senthooran et al. 2016, Bandyopadhyay, Chung et al. 2017, Oh, Ramezan Shirazi et al. 2017, Valentini, Ferrante et al. 2017, Suárez, Iglesias et al. 2019, Schranz, Umlauft et al. 2020). A catalog of the most prominent swarm robotics projects was developed by (Schranz, Umlauft et al. 2020) and is the basis for Table 2. Connecting vehicles on the road is a harder problem than what has been achieved in swarm robotics as robotic swarms are on local networks in close proximity where all robots have access to location data of all other robots with a fundamentally noiseless operating environment (Soysal and Şahin 2006). Connecting real-world automotive vehicles pose several unique challenges that swarm robotics has not addressed such as:

- Highly regulated traffic laws (lanes, signs, lights, etc.),

- Interactions with high diversity of vehicles,
- Interactions with vehicles that may or may not be connected in any manner, and
- Noisy environment with moving non-vehicle objects (i.e. pedestrians).

While swarm robotics may on its face appear related and similar to the problem of connected vehicles, swarm robotics is not a useful or relevant field for this research based on the aforementioned points of divergence.

Table 2. Detail of swarm robotics projects.

Project Name	Robot Type	Application	Environment	# of Robots
Kilobots	UGV	Research and Education	Terrestrial	1,024
Jasmine	UGV	Research and Education	Terrestrial	60
Alice	UGV	Research and Education	Terrestrial	20
AMiR	UGV	Research and Education	Terrestrial	6
Colias	UGV	Research and Education	Terrestrial	14
Mona	UGV	Research and Education	Terrestrial	30
R-One	UGV	Research and Education	Terrestrial	N/A
Elisa-3	UGV	Research and Education	Terrestrial	38
Khepera IV	UGV	Research and Education	Terrestrial	10
GRITSbot	UGV	Research and Education	Terrestrial	100
E-Puck	UGV	Research and Education	Terrestrial	16
Xpuck	UGV	Research and Education	Terrestrial	16
Thymio II	UGV	Research and Education	Terrestrial	8
Pheeno	UGV	Research and Education	Terrestrial	4
Spiderino	UGV	Research and Education	Terrestrial	N/A
I-Swarm	UGV	Research and Education	Terrestrial	N/A
Zooids	UGV	Research and Education	Terrestrial	32
APIS	UGV	Research and Education	Terrestrial	6
Wanda	UGV	Research and Education	Terrestrial	11
Droplet	UGV	Research and Education	Terrestrial	N/A
Swarm-bot	UGV	Research and Education	Terrestrial	35
Swarmanoid	UGV	Research and Education	Terrestrial	N/A
Termes	UGV	Research and Education	Terrestrial	5
Symbrion and Replicator	UGV	Research and Education	Terrestrial	N/A
PolyBot	UGV	Research and Education	Terrestrial	32
M-Tran III	UGV	Research and Education	Terrestrial	24
ATRON	UGV	Research and Education	Terrestrial	7
CONRO	UGV	Research and Education	Terrestrial	8
Sambot	UGV	Research and Education	Terrestrial	15
Molecube	UGV	Research and Education	Terrestrial	8
SwarmBot 3.0	UGV	Agriculture	Terrestrial	5
Xaver	UGV	Agriculture	Terrestrial	10
GUARDIANS	UGV	Emergency and Rescue	Terrestrial	4
Ocado, Amazon (Kiva), Alibaba	UGV	Warehouse	Terrestrial	1,100
SWILT	UxV	Industrial Plant	Terrestrial	1,500

Project Name	Robot Type	Application	Environment	# of Robots
MAV	UAV	Research and Education	Aerial	N/A
Distributed Flight Array	UAV	Research and Education	Aerial	9
Crazyflie 2.1	UAV	Research and Education	Aerial	49
FINken-III	UAV	Research and Education	Aerial	N/A
OFFSET	UGV, UAV	Military	Aerial	250
Perdix	UAV	Military	Aerial	103
SMAVNET	UAV	Emergency and Rescue	Aerial	19
SWARMIX	UAV	Emergency and Rescue	Aerial	N/A
CPSwarm	UAV	Emergency and Rescue	Aerial	N/A
SAGA	UAV	Agriculture	Aerial	N/A
Spaxel	UAV	Entertainment	Aerial	100
Flyfire	UAV	Entertainment	Aerial	N/A
Ehang GhostDrone 2.0	UAV	Entertainment	Aerial	1,000
Intel Shooting Star	UAV	Entertainment	Aerial	500
Lucie micro drone	UAV	Entertainment	Aerial	N/A
CoCoRo	UUV	Environmental Monitoring	Aquatic	41
Monsun	UUV	Environmental Monitoring	Aquatic	N/A
CORATAM	USV	Environmental Monitoring	Aquatic	12
Platypus	USV	Environmental Monitoring	Aquatic	25
Apium Data Diver	USV, UUV	Environmental Monitoring	Aquatic	50
subCULTron	UUV	Environmental Monitoring	Aquatic	N/A
Vertex Swarm	UUV	Environmental Monitoring	Aquatic	10
SWARMs	UUV, USV	Environmental Monitoring	Aquatic	8
CARCaS	USV	Military	Aquatic	5
ROBORDER	UxV	Surveillance	Terrestrial, Aerial, Aquatic	N/A
BugWright2	UxV	Maintenance	Terrestrial, Aerial, Aquatic	N/A
Sentien Robotics	UGV, UAV	Multiple	Terrestrial, Aerial, Aquatic	N/A
Swarmies	UGV	Space Exploration	Outer Space	20
Marsbee	UAV	Space Exploration	Outer Space	3
Swarm	UAV	Space Exploration	Outer Space	3
Cluster II	UAV	Space Exploration	Outer Space	4

2.5 The Economics of Automotive Industry in Relation to ADAS

The US automotive industry in 2019 manufacturing was valued at $643.9B (Maike Schlumbohm 2020) while earning a revenue of $1,252.4B (Statista 2020). This accounts for 3% and 6% of the Gross Domestic Product of the United States for 2019 which was $21,427.7B (Economics 2020, Bank 2021). For perspective, the automotive industry's revenue is comparable to the total GDP of Russia.

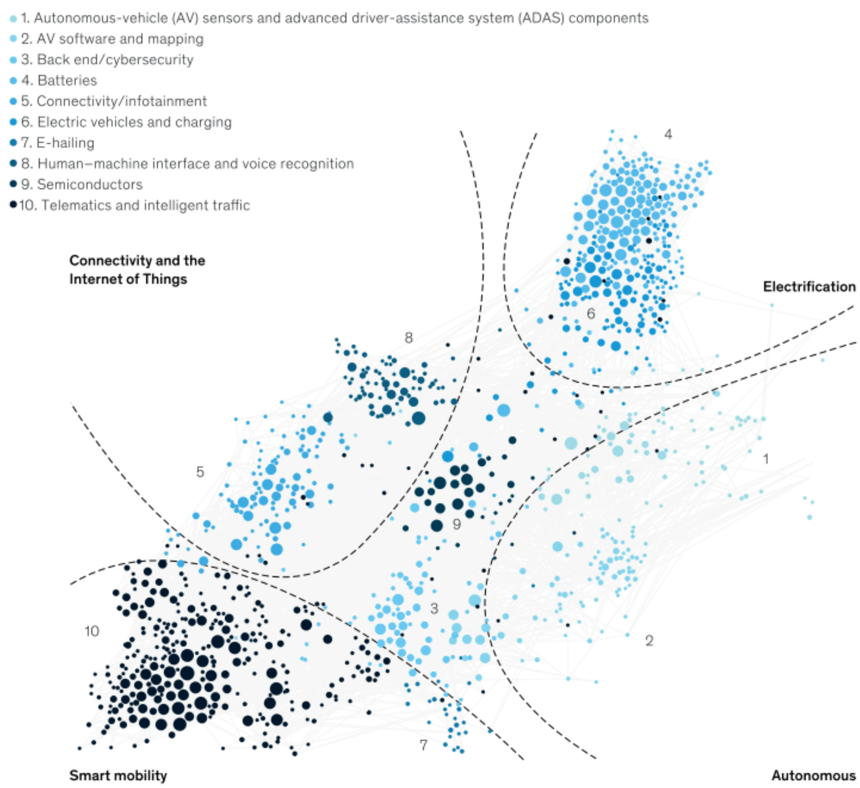

Figure 4. Mapping of investment activities across 10 automotive clusters (Statista 2020).

The automotive industry is currently making sizable investments ($220B since 2010) in new technologies across ten clusters, which can be grouped into four main areas of research – Electrification, Connectivity and the Internet of Things, Smart Mobility, and Autonomy – as shown in Figure 4 (Daniel Holland-Letz 2019). Of the $220B invested since 2010 more than $29.9 billion has been invested by companies into ADAS technology research with averages each year ranging from $0.6 billion in 2010 to $5.6 billion in 2019 (Daniel Holland-Letz 2019). The total investment is expected to increase to over $91.8

billion by 2025 (Markets 2020). A total of 9,100 patents have been filed with most coming out of the US, China, and the UK (Daniel Holland-Letz 2019).

Table 3. Average Economic Cost by injury severity taken from 2018 (Council 2020).

Injury Level	Cost	Injury Level (#)
Death (K)	$1,659,000	4
Disabling (A)	$96,200	3
Evident (B)	$27,800	2
Possible (C)	$22,800	1
[illegible]	[illegible]	[illegible]

Economic importance of ADAS is more than just the cost of investment. The cost associated with accidents need strong consideration when evaluating the economics of ADAS. The level of injury influences the cost associated with accidents. An accident resulting in a fatality on average costs $1.7M (National Safety Council 2020). Table 3 shows a breakout of cost for the varying severities of injuries based on (National Safety Council 2020). Finding ways to reduce fatalities is very important and ADAS has potential to do so. At the same time, ADAS is becoming more complex and with the added complexity comes added upkeep and repair costs. The upfront cost the consumer to have a vehicle equipped with ADAS is approximately 5% - 15% the total cost of the vehicle (Automotive 2019). The cost to have these systems repaired has ballooned as depicted in Table 4. In some cases, the cost for repair of ADAS capable parts has doubled while in

Table 4. Cost of vehicle part repairs/replacements based on (Association 2018, Preston 2020). Max cost represents ADAS vehicles while min cost is without ADAS.

Component	Max Cost ($)	Min Cost ($)
Front Bumper	4300	1450
Rear Bumper	4550	1950
Side Mirror	2750	1250
Head- & Tail- lights	1750	300
Windshield	3650	1750

more extreme cases increased by over twelve times the cost for a non-ADAS version of the part (Association 2018, Preston 2020).

2.6 Trucks

Trucks represent 56% of all registered vehicles in the United States (Administration 2019) with FSLDPT comprising 18% (Company 2020). With FSLDPTs contributing to a significant portion of vehicles in the U.S. this represents an opportunity area that has yet to be explored for the effectiveness of ADAS at reducing injury severity. Heavy trucks on the other hand, were some of the first vehicles to decades ago to integrate ADAS technology. Heavy trucks have been broadly studied for how ADAS has improved their safety.

2.6.1 Heavy Trucks

Heavy trucks represent a wide range of vehicles from service vehicles to buses to tractor trailers or freight trucks. They are defined by their Gross Vehicle Weight Rating (GVWR) >26,001 lbs. and are labeled as Class 7 and 8 vehicles by the Federal Highway Administration (FHWA) and Environmental Protection Agency (EPA) (Federal Highway Administration (FHWA) 2012). Commercial trucks represent 13.7% of all registered vehicles in the United States (Gaaille 2018, Associations 2020). Commercial freight trucking grossed $791.7B in 2019, which accounts for over 11.84B tons of freight or 72.5% of all freight in the US (Associations 2020). Combined 184.2B miles were driven in 2018 (Associations 2020). Heavy trucking literally drives the US economy, and for this reason a large amount of research has been invested into heavy trucks.

Heavy trucks were some of the first vehicles to integrate ADAS technologies due to their commercial uses back in the 1990s (Kunze, Haberstroh et al. 2011). Many ADAS technologies were first tested and developed for heavy trucks such as lane keeping (LK) (Montiglio, Martini et al. 2006). ADAS has been proposed to have the potential to be more effective in heavy trucks than light vehicles under ideal driving conditions (Yue, Abdel-Aty et al. 2019). They also are now the first vehicles to have connected ADAS in the forms of cooperative adaptive cruise control (CACC) (Cafiso and Di Graziano 2012, Müller 2012). The advantage to platooning, V2V, is financially driven in that it reduces energy consumption and emissions and reduces driver fatigue (Tsugawa, Jeschke et al. 2016). Fatigue is a leading cause of human error, which the WHO has determined is the leading cause of automotive accidents (Peden, Scurfield et al. 2004). Because of the financial importance of heavy trucks on economies, they have been studied in depth for accident prevention and do not present as rich of an opportunity for new research as FSLDPTs.

2.6.2 Full-Size Light-Duty Pickup Trucks (FSLDPTs)

Table 5: ADAS technology offerings by model from 2015 to 2020, split between standard and optional offerings (latter in parentheses).

	Model Year					
ADAS Feature:	2015	2016	2017	2018	2019	2020
Adaptive Cruise Control	(F)	(F)	(HR, F)	TU, (HR, F)	TU, (HR, F)	TU, (HR, NT, GS, CS, F)
Rear View Camera	CS, TU, (R, GS, F)	CS, TU, (R, NT, GS, F)	CS, TU, (R, NT, HR, GS, F)	A	A	A
Blind Spot Monitoring	(TU, F)	(NT, TU, F)	(NT, TU, F)	(NT, HR, TU, F)	(R, NT, HR, GS, CS, TU, F)	(R, HR, GS, CS, TU, F)
Cross Traffic Alert	(TU, F)	(NT, TU, F)	(NT, F)	(NT, HR, TU, F)	(R, NT, HR, GS, CS, TU, F)	NT, (HR, R, GS, CS, TU, F)
Forward Sensing System	(R, GS, CS, TU, F)	TU, (R, GS, CS, F)	TU, (R, HR, GS, CS, F)	TU, (R, HR, GS, CS, F)	TU, (R, HR, GS, CS, F)	NT, TU, (R, HR, GS, CS, F)
Lane Departure Warning	(GS, CS, F)	(GS, CS, F)	(HR, GS, CS, F)	TU, (HR, GS, CS, F)	TU, (R, HR, GS, CS, F)	NT, TU, (R, HR, GS, CS, F)
Forward Collision Warning w/Brake Support	NT, TU, (F)	NT, TU, (F)	NT, TU, (HR, GS, F)	NT, TU, (HR, GS, CS, F)	NT, TU, (R, HR, GS, CS, F)	NT, TU, (R, HR, GS, CS, F)
Reverse Sensing System	(R, CS, TU, F)	(R, CS, F)	(R, CS, F)	(R, CS, TU, F)	(R, GS, CS, TU, F)	NT, (R, GS, CS, TU, F)
Adaptive LED Headlamps	F	F	F	F, (GS)	GS, F, (HR)	NT, GS, F, (HR)
Automatic High Beam	(NT, F)	(R, NT, CS, F)	(R, NT, HR, CS, F)	TU, (R, NT, HR, GS, CS, F)	TU, (R, NT, HR, GS, CS, F)	NT, TU, (R, HR, GS, CS, F)
Active Park Assist	(R, CS, TU, F)	(R, GS, CS, TU, F)	(R, GS, CS, TU, F)	(R, GS, CS, TU, F)	(R, GS, CS, TU, F)	(R, GS, CS, TU, F)
360 Degree Camera	(F)	(NT, F)	(NT, F)	(NT, F)	(R, NT, GS, F)	(R, NT, GS, F)
Lane Keeping System	(F)	(GS, CS, F)	(HR, GS, CS, F)	(HR, GS, CS, F)	(R, HR, GS, CS, F)	(R, HR, GS, CS, F)
Adaptive Cruise Control with Stop and Go			(F)	TU, (F)	TU, (R, F)	NT, TU, (R, F)
Hill Start Assist	R, F, (GS)	R, NT, F, (GS)	R, NT, F	R, NT, GS, F, (HR)	R, NT, GS, F, (HR, TU)	R, NT, GS, F, (HR, TU)
Driver Fatigue Alert			(F)	(F)	(F)	NT, (F)
Enhanced Active Park Assist			(F)	(F)	(R, F)	(R, F)
Hill Descent Control	(GS, F)	(NT, GS, F)	(R, NT, GS, F)	(R, NT, GS, F)	(R, NT, GS, TU, F)	(R, NT, GS, TU, F)
Adaptive Cruise Control with Stop and Go and Lane Centering					(F)	(F)
Evasive Steering Assist					(F)	(F)
Pre-Collision Assist with Automatic Emergency Braking					(R, GS, CS, F)	NT, (R, GS, CS, F)
Post Collision Braking					(F)	(F)
Reverse Brake Assist					(GS, F)	(GS, F)
Speed Sign Recognition						(NT, F)

Key: CS = Chevy Silverado; NT = Nissan Titan; R = Dodge RAM 1500; GS = GMC Sierra; HR = Honda Ridgeline; TU = Toyota Tundra; F = Ford F-150; A = All

The high percentage (18%) of registered FSLDPTs in the US (Administration 2019) makes it critical to examine how the integration of ADAS has affected fatalities and injuries in accidents these vehicles. Unlike the heavy trucks, which are for commercial use, have massive blind spots, and can weigh 3 times as much, FSLDPTs are intended for personal use like sedans (Trigell, Rothhämel et al. 2017). FSLDPTs unlike sedans are larger, less maneuverable, and they tend to have larger blind spots (ConsumerReports 2014). These characteristics make the potential benefit from ADAS even more impactful. FSLDPTs have a GVWR of 6,001 to 10,000 lbs. and are categorized as Class 2 vehicles by the FHWA and EPA (Federal Highway Administration (FHWA) 2012). In this category are the Chevrolet Silverado 1500, Dodge RAM 1500, Ford F-150, GMC Sierra 1500, Honda Ridgeline, Nissan Titan, and Toyota Tundra. ADAS has in recent years been incorporated into FSLDPTs; originally being reserved as options, they are becoming ever more a standard making them a ripe segment of vehicles to use for analysis. A breakdown of ADAS in FSLDPTs is given in Table 5.

2.7 Literature Review Summary

With the incredible amount of expenditure automotive manufacturers are investing to develop better and safer vehicles ($220B) (Daniel Holland-Letz 2019), they have brought the industry as a whole from level 0 autonomy at the start of the 2000s to level 2 autonomy on the verge of level 3 in just 20 years (KBB 2020). The instrument to continue the advancement of vehicle autonomy is CV with V2V communication (KBB 2020). Which vehicles are tethered for a local network and what is transferred amongst them will be critical for the success of CVs along with acceptance rate. Biologically inspiration for how to plan these local networks for CVs provide a unique and optimized strategy for connecting vehicles (e.g. spacing of vehicles and what is communicated between vehicles).

For developing these models, the vehicle platform will play a major role in the success of the model. The FSLDPT offers a unique advantage for model creation as it represents 18% of registered vehicles in the US (Administration 2019), and their design imposes larger blind spots and greater mass than sedans increasing the lethality during accidents (ConsumerReports 2014).

CHAPTER 3. EVALUATION OF DRIVING: HOW THE ACT IS PERFORMED AND WHAT IS INVOLVED

With over 240 million registered vehicles in the United States (Fish and Bras 2021), most Americans ages 16 and over are fairly acquainted with driving. Even with so many Americans driving, the true understanding of the act is likely vague due to misconceptions in how their mental models of driving are formed (Fish, Murphy et al. 2019). This chapter establishes a common understanding of the feat of driving. Here functional diagrams of function trees and functional decompositions along with flow diagrams and other figures are employed to construct the common understanding used for this dissertation.

3.1 General Overview of Driving

Driving is the act of transferring oneself under the power of one's own guidance from one location to another using a mechanized means of locomotion. The driver first selects the destination then the route to the destination. The driver then moves the in the vehicle along the route to the destination. A diagram of this process is shown in Figure 5.

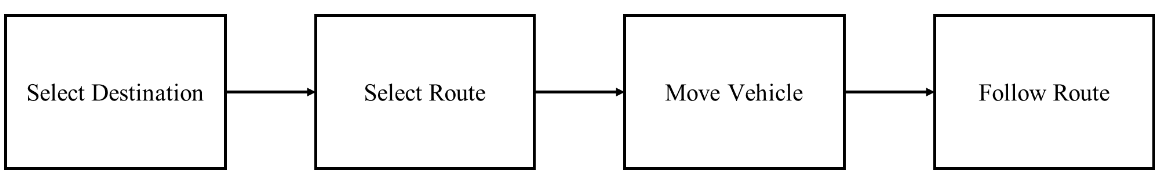

Figure 5. Flow diagram for the simplified driving process.

On the road drivers will interact with other drivers, obstacles, and traffic patterns/configurations. These tasks are affected by deprecations in weather and lighting. Also, there are other ill-advised deprecations of cognition caused by drug or alcohol intoxication. Sensory awareness is a crucial component to navigating successfully through all the responsibilities incumbent on the driver. A number of authors (Amersbach and Winner 2017, Amersbach 2020, Philipp, Schuldt et al. 2020) have developed a functional decomposition of the automation for driving based on human interpretations of these tasks as shown in Figure 6. They follow a modified Plan Do Check Act Cycle which they refer to as their Sense-Plan-Act-Paradigm (Philipp, Schuldt et al. 2020). With Figure 6 there is a noticeable linear process from information acquisition and comprehension to response with vehicle motion.

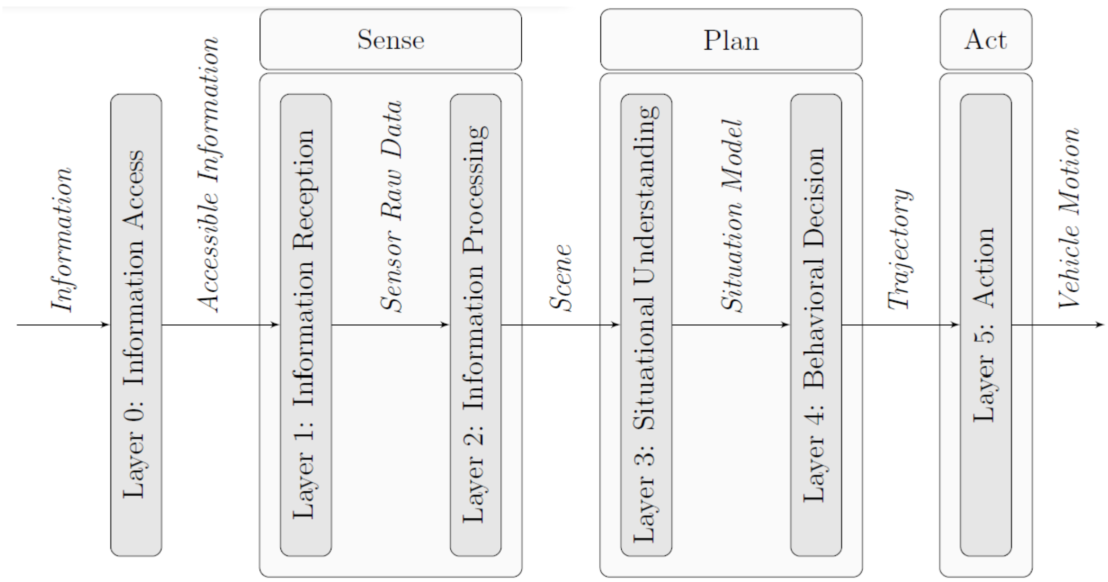

Figure 6. Functional decomposition of driving systems charted using the Sense-Plan-Act-Paradigm (Amersbach and Winner 2017, Philipp, Schuldt et al. 2020).

Most sensory information a driver incorporates into their decision for how to respond to the conditions of their driving environment comes from their visual inspection of what is in front of them with occasional inspection of what is adjacent to them on either side. From the driver's observation of the environment, they will perform one or more of the subsequent actions when appropriate: accelerate, travel at a constant speed, decelerate, or change lanes (Zhang, Chan et al. 2011). At times these decisions are intrinsically flawed due to a deficiency of information from the observation of the driver. This is one area where ADAS sensors compliment the driver by providing increased sensory awareness. Intuitively the driver is checking they are maintaining a safe distance from vehicles in front of their vehicle. ADAS or ADS can take in much of the same data and using basic Newtonian physics maintain minimal spacing as described by Equations 1 and 2 (Nguyen and Ho 2016). Equation 1 calculates the safest minimal distance between two consecutive longitudinal vehicles, while Equation 2 calculates the minimal safe distance between transverse vehicles. ADS provides additional benefit as it dissimilar to human drivers and does not feel the need to decrease speed in narrow lanes (Pinjari, Augustin et al. 2013). The reason for this is likely the human driver is judging the rate of speed by optic flow similar to birds, fish, and insects (Scholtyssek, Dacke et al. 2014, Crall, Ravi et al. 2015). Here a narrow lane means in the mind of the driver that the objects in the periphery are moving apparently faster and in response the human driver slows down because of this feedback. Thus, human sensory information is not always reliable because of how humans acquire and process the information, and this bolsters the importance for determining which signals are most reliable to animals that could improve ADS.

$$d_{longitudinal} = \frac{l*\upsilon}{\upsilon_{max}} + \delta \tag{1}$$

$$d_{tranverse} = \frac{w*\upsilon}{\upsilon_{max}} + \Delta \tag{2}$$

- Length of the vehicle denoted by l.
- Width of the vehicle denoted by w.
- Current traveling speed denoted by υ.
- Speed limit denoted by υ_{max}.
- δ: Minimum distance between two stopped in lines longitudinal vehicles
- Δ: Minimum distance between two stopped transverse vehicles

Two aspects of interest as it relates to driving for the purposes of this dissertation are how a crash is avoided and what leads to the occurrence of a crash. These aspects of driving safety are decomposed in the subsequent parts of this chapter.

3.2 Crash Avoidance

Traffic pattern organization is stated to be a NP hard problem due to the various rules, laws, and volume of vehicles involved with driving (Khan, Aadil et al. 2018). Avoiding a crash is a significant aspect of a successful trip. Many authors have created simulations, experimented, and written papers about why their research/technology improves safety or reduces automotive crashes. Few functionally decompose their research/technology to the essences for how it integrates with the vehicle and driver (Amersbach and Winner 2017, Amersbach 2020, Philipp, Schuldt et al. 2020). Unlike Figurers 5 and 6, which are generic and topical, (Amersbach 2020) functionally decomposed Adaptive Cruise Control (ACC) in detail as shown by the function tree in Figure 7.

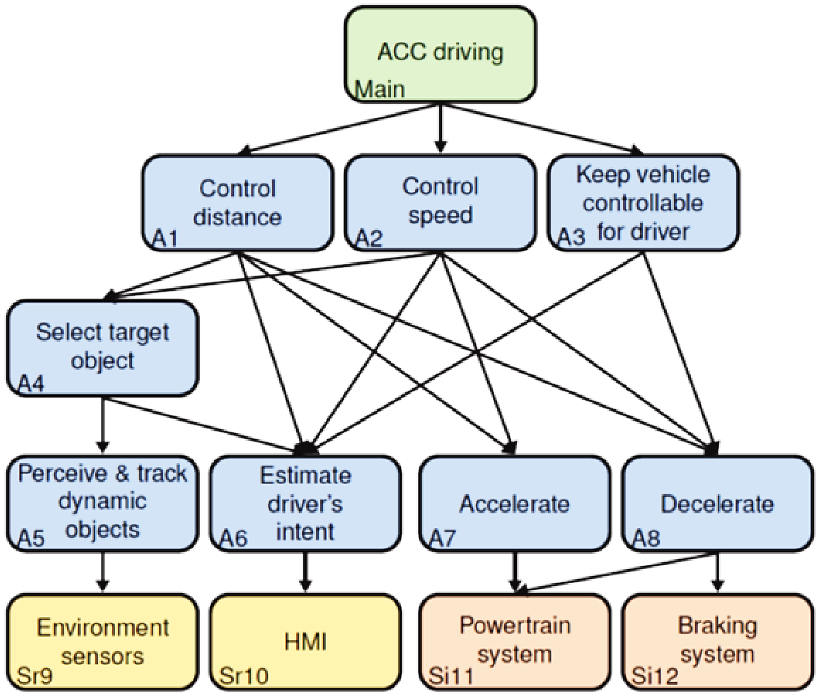

Figure 7. Adaptive cruise control function tree (Amersbach 2020).

Figure 7 is a useful functional decomposition for a specific ADAS technology, but there is a gap for the overarching functional decomposition for how ADAS works. Figure 8 accomplishes the overlooked task of an overarching functional decomposition for how ADAS works by use of a function tree. It functionally decomposes how ADAS detects objects and features in the environment and directs the vehicle to avoid crashes.

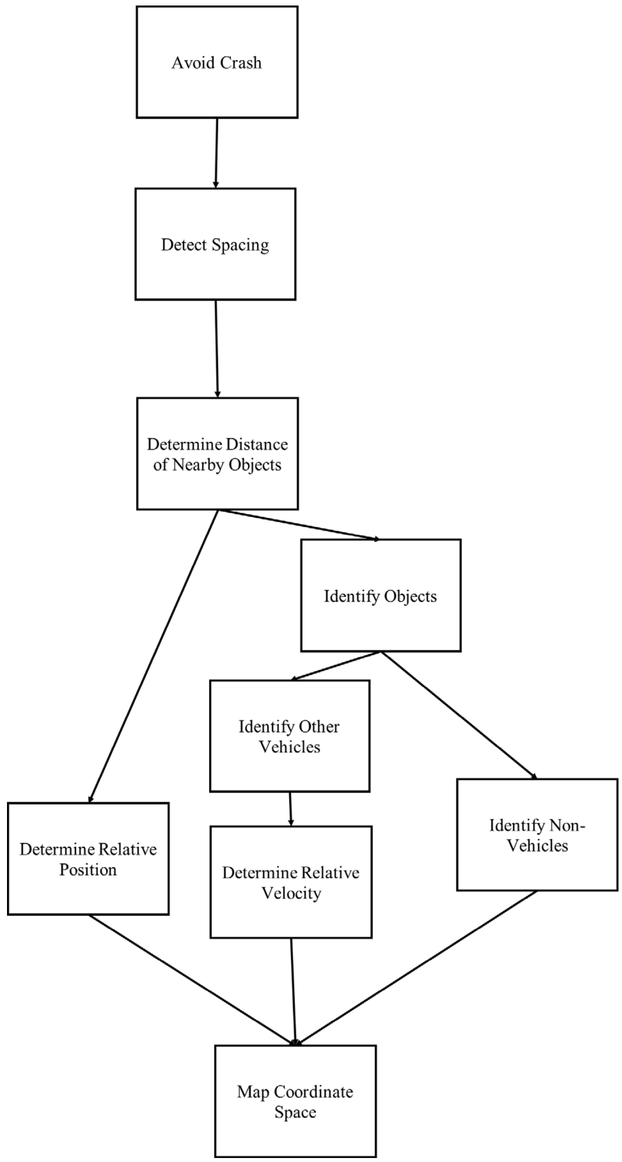

Figure 8. Function Tree of ADAS.

An example of one way the function tree of Figure 8 and the flow diagram of Figure 5 could potentially be integrated into an actual vehicle is depicted in Figure 9. For this a system/driver would be following traffic laws, the vehicle's GPS, and ADAS to avoid a crash and successfully transport to their destination. In Figure 9 the proposed method has the ADAS branch of the function tree indirectly influencing the routing branch, for the ADAS map of coordinate space is observed by the routing branch. The observation of coordinate space feeds into the predict crash branch. The predict crash branch in turn has an underlining logic flow diagram for determining how the vehicle should move away from the potential crash as shown in Figure 10. It is here that a possible set up for networking of connected vehicles is seen. Figure 10 is a system of systems, breaking the responses to a potential crash into 3 strata of interactions: smart to smart, smart to semi-smart, and smart to dumb. As it takes decades for older vehicles to phase out of the vehicle fleet it is a reality that smart vehicles will likely be on the road with different connectivity levels of vehicles.

- Smart to Smart – both vehicles are able to send and receive information.
- Smart to Semi-smart – one of the vehicles is only able to send information but is unable to receive information while the other has both means of transition available.
- Smart to Dumb – one of the vehicles cannot transmit any information at all while the other has both means of transition available.

In the Smart to smart case, a field bargaining problem emerges where an optimal solution can be achieved through cooperation of both parties involved (Nash 1950). In the smart to semi-smart case the smart vehicle would use the information to take the best action for itself. Much like the analogous case of animal flocks where communication is needed because animals cannot sense equally as well in all directions. Finally, in the smart to dumb situation traditional ADAS would be relied upon for crash prevention.

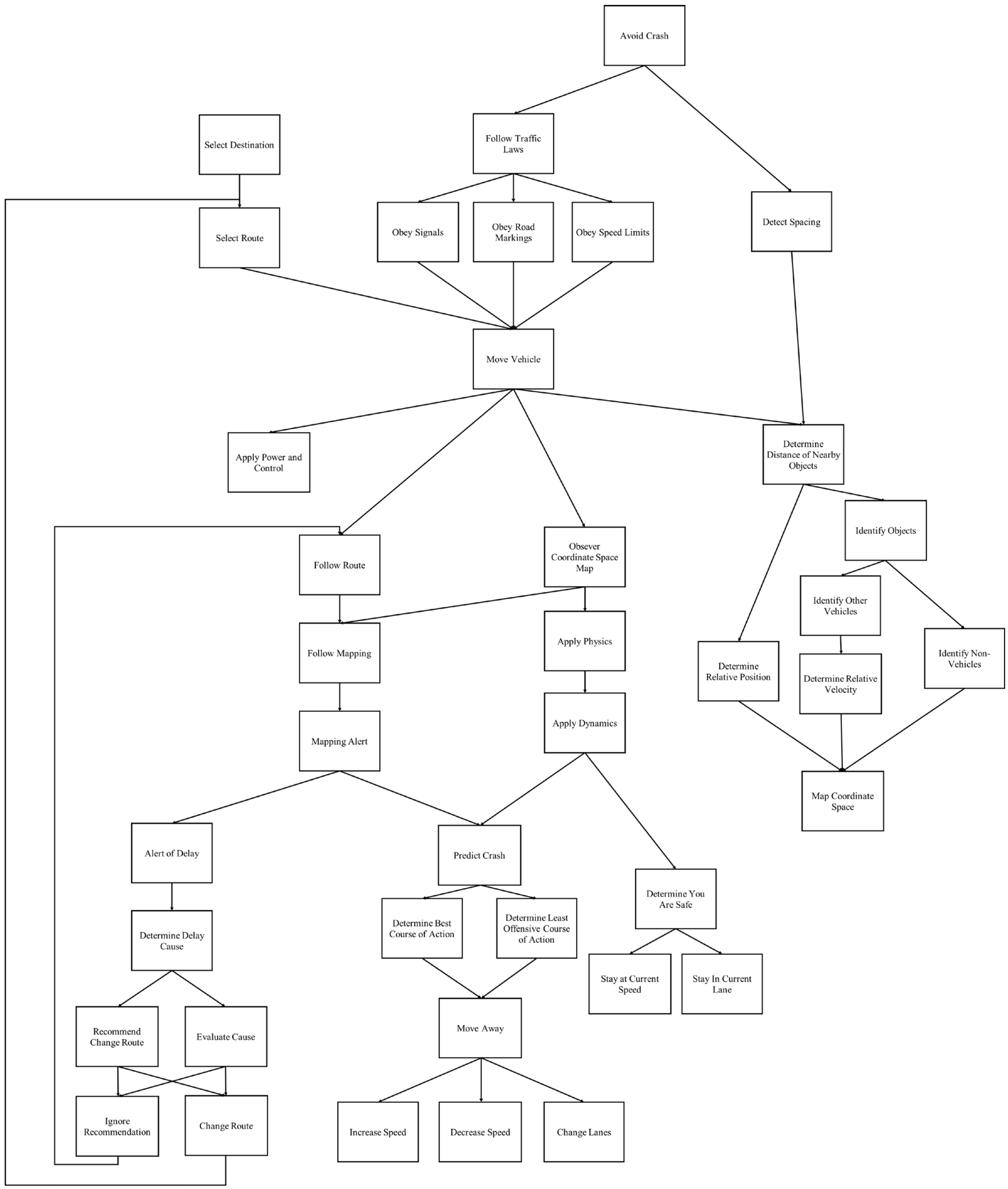

Figure 9. Function tree of one way a system/driver may integrate ADAS.

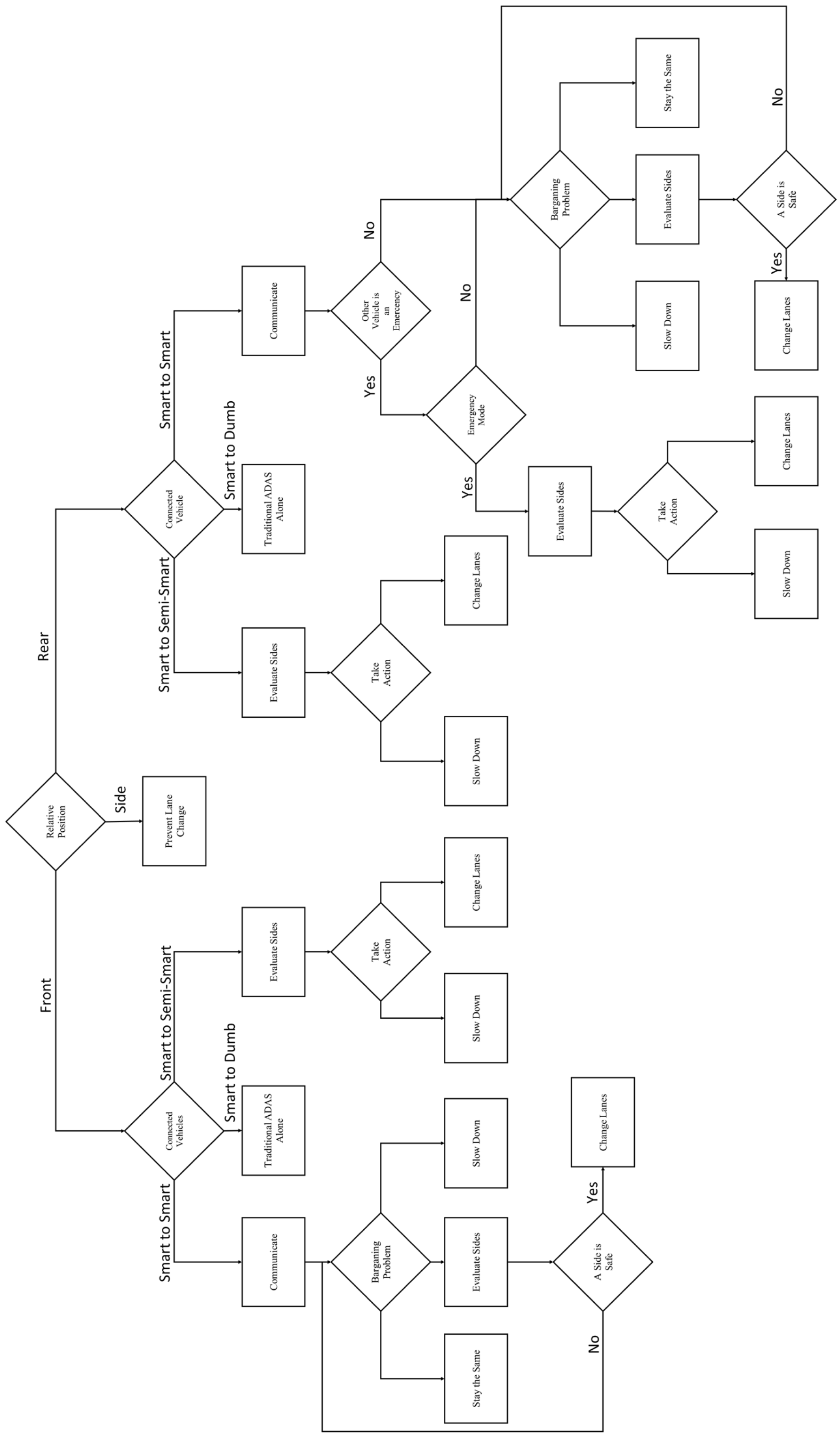

Figure 10. Logic flow diagram for determining how to move to avoid a crash.

From the functional decomposition of ADAS as shown in Figure 8, several of the elements can be looked at for biological inspiration. First, appropriate questions should be posed for those elements of interest from a biological perspective.

- Detect Spacing – Do animals detect there is enough space?
- Detect Spacing – How do they determine what is enough space?
- Determine Distance of Nearby Objects – How do they determine the relative distance of nearby objects?
- Identify Objects – How do they identify objects?
- Identify Objects –What other animals/objects they should pay attention to around them?
- Identify Objects – How do they deal with potential blind spots?
- Identify Objects – Determining of friend, prey, or predator?
- Determine Relative Position – How do they orient themselves in space?
- Determine Relative Velocity – How do they determine how fast another animal is moving?
- Determine Relative Velocity – Is this where they determine a collision will happen?

Likewise, when planning out how to connect the vehicles for passing information to assist ADAS in preventing accidents, as proposed in this dissertation, a functional decomposition should be developed to inspect elements and ask similar questions of it for how biology performs these tasks. Figure 11 shows just such a function tree for connecting ADAS between vehicles.

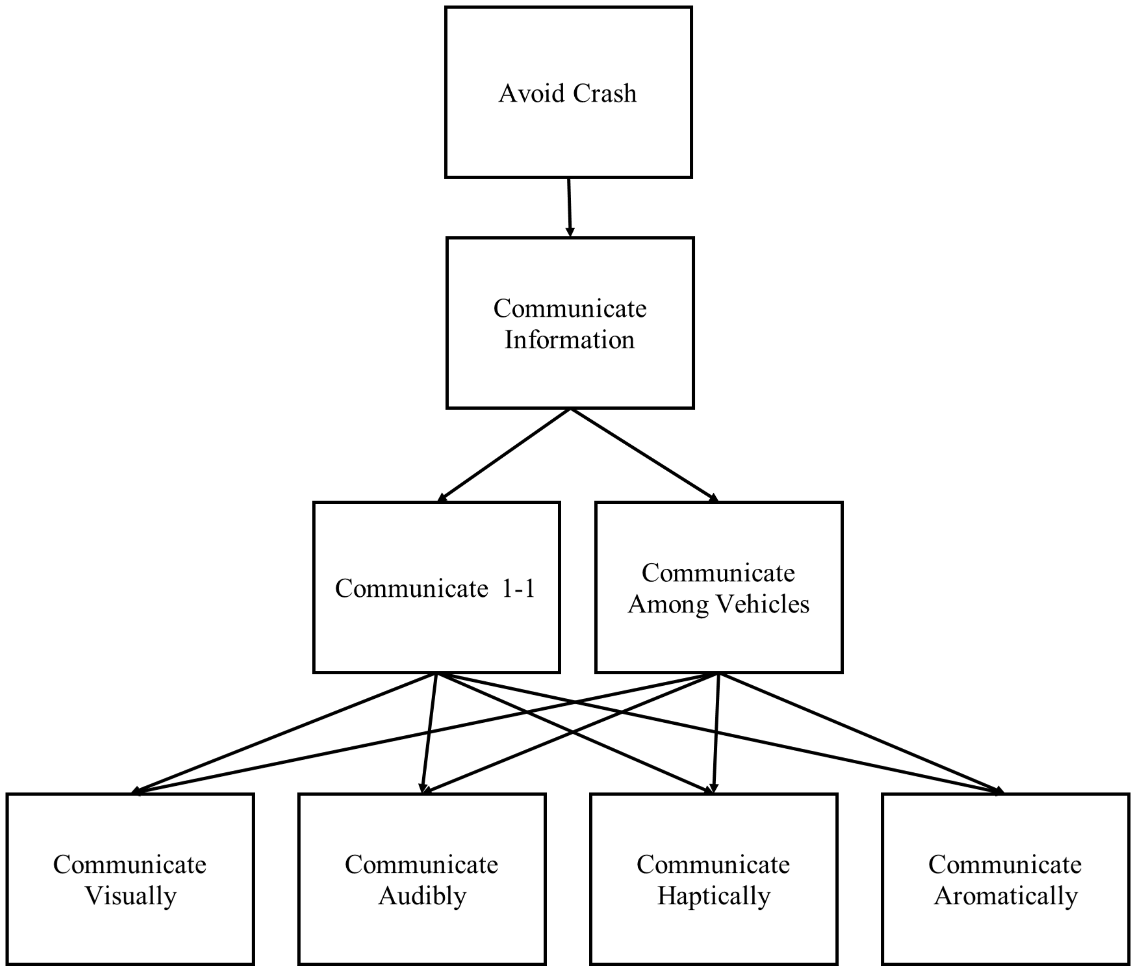

Figure 11. Function tree for connected ADAS.

Here in Figure 11 different levels of the function tree pose biological questions.

- Communicate 1-1 vs Among Vehicles - How is it decided if to communicate 1-1 or to a group?
- Communicate Visually/Audibly/Haptically/Aromatically – How does biology do these tasks?
- Communicate Visually/Audibly/Haptically/Aromatically – When do they choose to do one vs the other?

- Communicate Visually/Audibly/Haptically/Aromatically – Is there a preference for one type situationally?

These questions of biology for both the ADAS function tree and the connected ADAS function tree, Figures 8 and 11 respectfully, were evaluated and are answered in Chapter 6. Based on the background of the biology literature review aromatic communication is likely not useful for the purposes of this research, but it was an avenue worth examining if only to eliminate it as a viable means of communication.

Avoiding a crash can be treated as a black box with the vehicle, people, energies, and signals being input with the vehicle, people, and energy being output as shown in Figure 12.

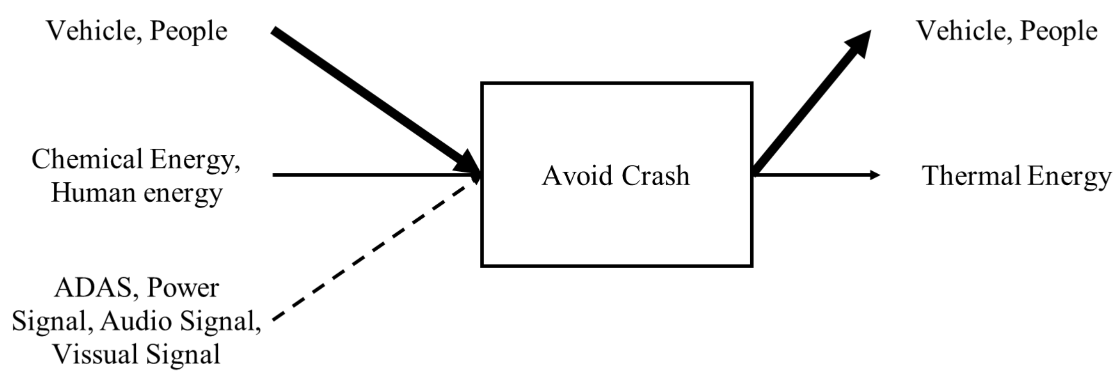

Figure 12. Black box for function Avoid Crash.

From this a traditional engineering design functional decomposition can be composed as shown in Figure 13. In Figure 13, there exists a conservation of mater and energy during the function of avoid crash.

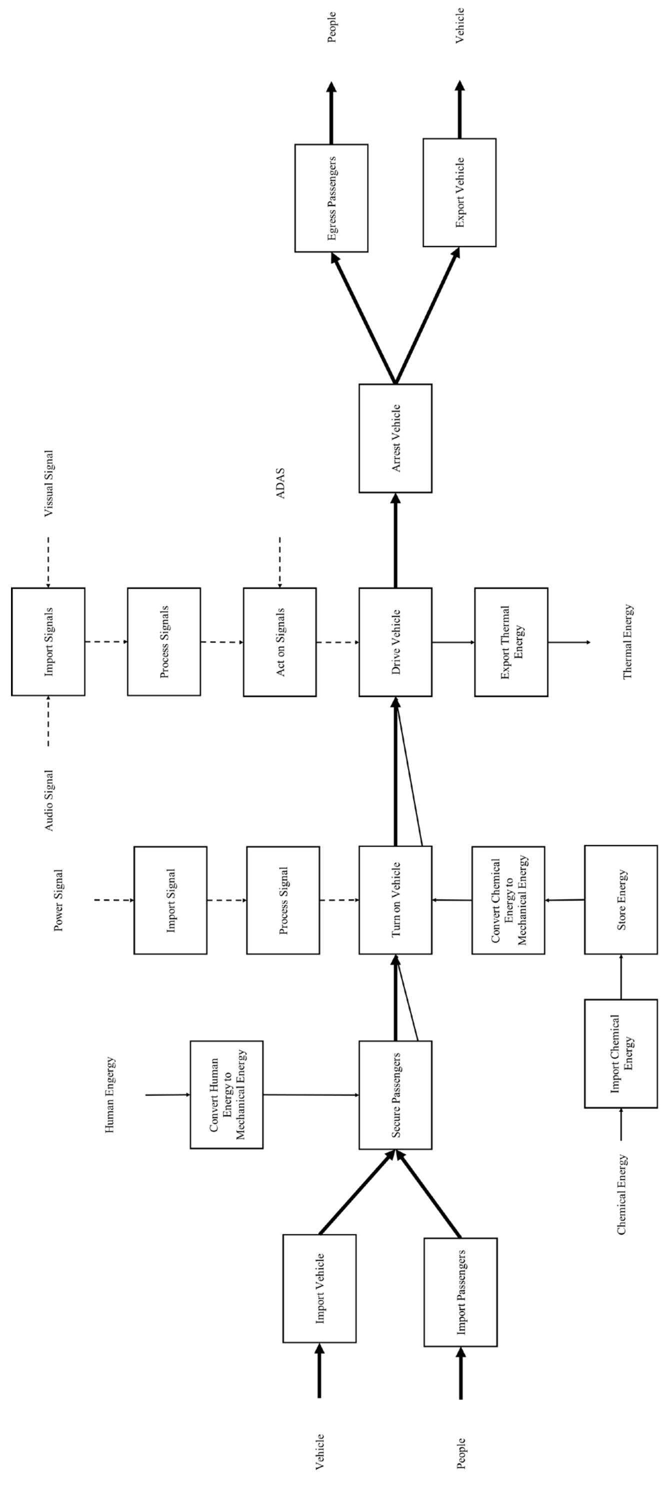

Figure 13. Engineering design functional decomposition for crash avoidance.

The function of avoid crash can be also defined to have the vehicle communicate with other vehicles through the use of exporting signals as shown by the black box of Figure 14. There the vehicles communicate through traditional means such as the audio and visual signal outputs such as horns and lights, but it also includes the novel output of a network signal. Now this work does not prescribe how the network is established be it LTE, 5G, Wi-Fi, or another network protocol.

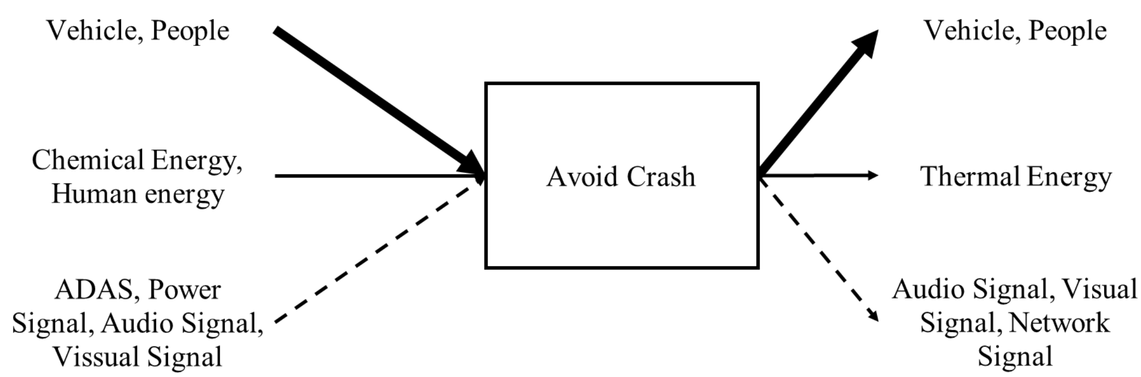

Figure 14. Black box for the function Avoid Crash with output signals.

As was the case of Figure 13 being associated with Figure 12, Figure 15 is too associated with Figure 14. In Figure 15, the engineering design functional decomposition of the function avoid crash is shown now including the export of signals so vehicles may communicate amongst themselves. The benefit of the systems depicted in Figure 15 over Figure 13 is the ability to transmit information to other vehicles. In this Figure 15 is a smart vehicle while figure 13 is a semi-smart vehicle.

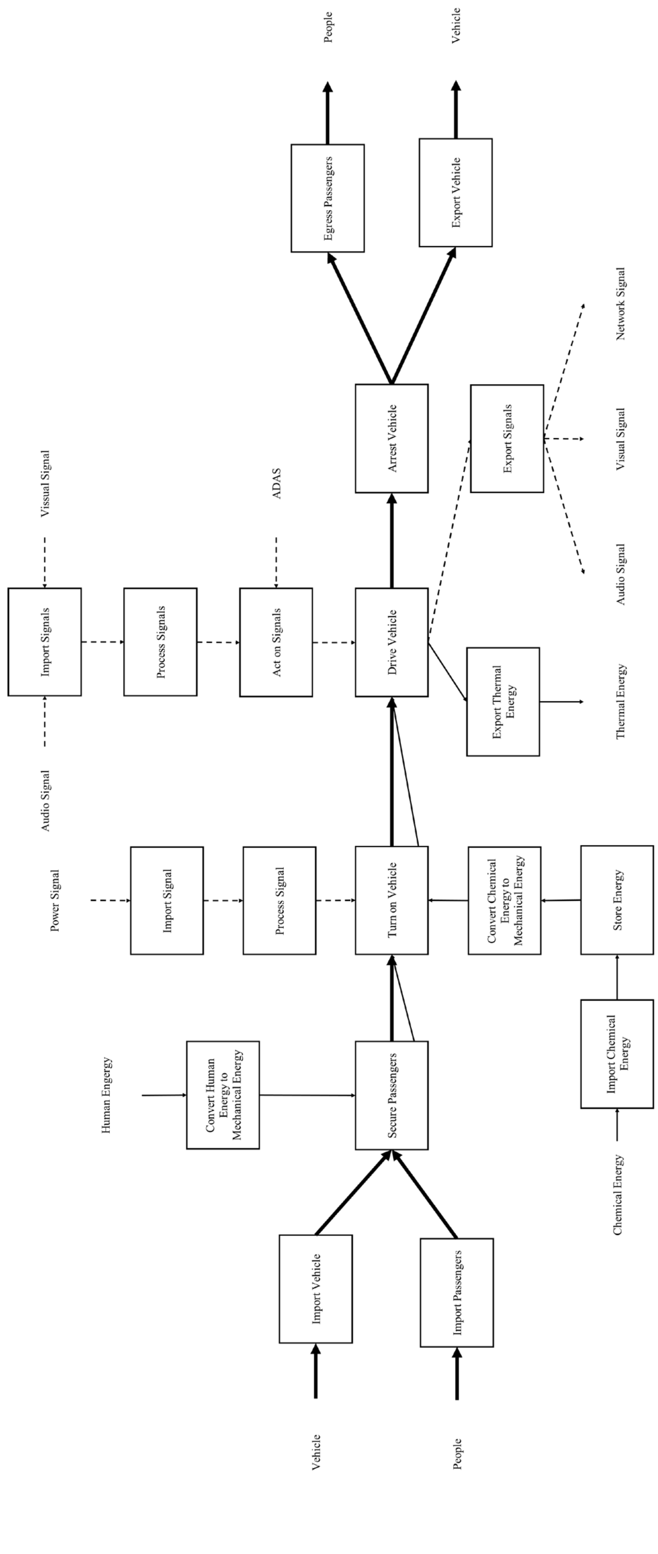

Figure 15. Engineering design functional decomposition for crash avoidance with export signals.

3.3 Anatomy of a Crash

Automotive crashes are complex and devastating events with many factors influencing the outcome. From the type of vehicles involved to road and weather conditions to who is driving all play roles in automotive crashes. Due to its pervasive use, the Ford F-150 with ADAS was the subject for examining crashes. Between the years 2016 and 2018 inclusively, in FARS, there were 98 unique F-150 crashes, 26 with a fatality and 72 without a fatality for an occupant of the F-150, examined both quantitatively and qualitatively. Instances were more than one injury were examined bringing the total of injuries evaluated to 138 with 31 fatalities and 107 lesser injuries. The quantitative discussion of these crashes is detailed in depth in Chapter 4.

Figure 16. Example of Google Earth images of a crash location.

For the qualitative analysis, GPS coordinates for each crash were search using Google Earth for both the satellite view of the road and the ground view images of the road and accompanying terrain as shown in Figure 16. The images were examined for observable features such as trees fences, straight road, curved road, etc. This was done for both groups of injuries for the three year period as shown in Table 6. The values were normalized by dividing the totals by the number of injuries for the two groups. A single factor ANOVA test was conducted between the normalized values of the two groups for which no statistical significance was found (P-value = 0.153). Meaning there was not a statistical difference in the qualitative observations for a fatal crash injury and a non-fatal crash injury.

Table 6. Qualitative observation of F-150 crashes 2016-2018. Note that fatal and non-fatal refer specifically to the occupants of that vehicle.

	Fatal Total	*Fatal Normalized*	*Non-Fatal Total*	*Non-Fatal Normalized*
trees	16	0.52	46	0.43
intersection	4	0.13	32	0.30
divider	2	0.06	10	0.09
field	7	0.23	6	0.06
fence	6	0.19	3	0.03
pole	5	0.16	25	0.23
house	4	0.13	2	0.02
no-shoulder	12	0.39	13	0.12
corn	3	0.10	0	0.00
backroad	4	0.13	7	0.07
two-lanes	16	0.52	9	0.08
gully	5	0.16	21	0.20
two-way	16	0.52	19	0.18
one-way	2	0.06	3	0.03
rural	3	0.10	2	0.02
narrow	10	0.32	16	0.15
shoulder	0	0.00	5	0.05
wall	0	0.00	6	0.06
residential	0	0.00	5	0.05
straight	1	0.03	11	0.10
curve	1	0.03	8	0.07
median	1	0.03	12	0.11

The month, day of the month, time, model year, person number (based on occupant total in vehicle during crash), seat position, age, sex, race, height, and license status for the driver the injured occupant were tracked. From the tracked occupant information time, seat position, and race were the only factors of significance during crashes. Time is distinguishable by it being light out or lack thereof light, seat position refers to which seat the occupant is positioned (driver seat, front passenger seat, etc.), and race is the ethnicity of the occupant (White, Black, Asian, etc.). For more details about those factors contributions on the outcome of a crash see Chapter 4.

With the observations of accident location and accident details a function tree was developed for understanding what leads to an automotive crash as shown in Figure X. It can be broken into two branches of what delays reaction time and what causes a poor judgement decision. Along the delayed reaction time branch the driver can be described as being either distracted or impaired. The impaired driver is a cause of prior poor judgement to the act of driving from either alcohol or drug usage. The distracted driver can be caused by visual, acoustic, or mental distractions. These can take different forms such as texting, noising passengers, day dreaming, etc. Along the other branch of judging a decision poorly can be thought of as a misjudgment of distance. That could be caused by not seeing a vehicle or not seeing the road. Both would be caused by deteriorated weather, poor lighting, or road geometry.

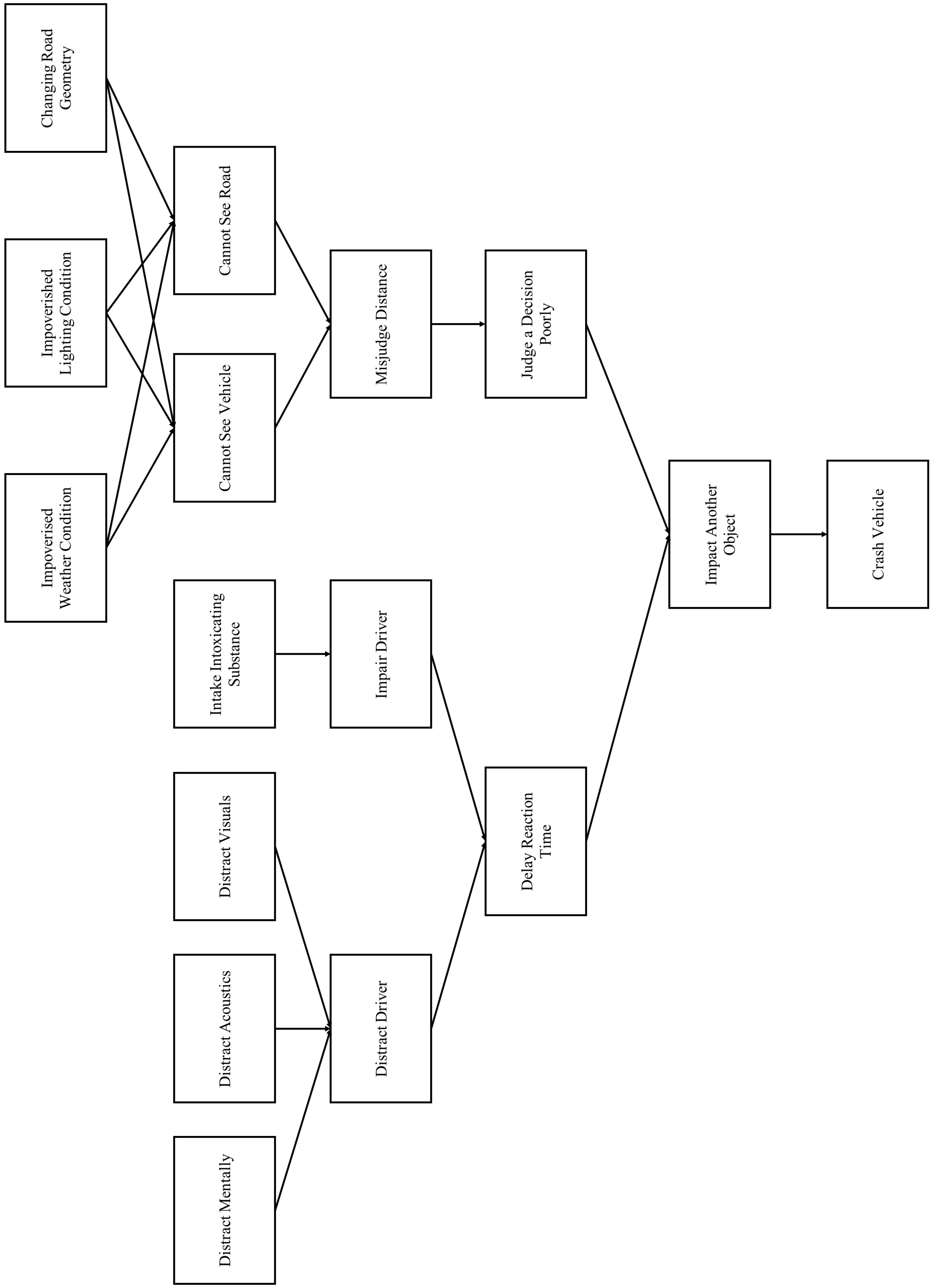

Figure 17. Function tree of crash causation.

CHAPTER 4. CURRENT FULL-SIZE LIGHT-DUTY PICKUP TRUCK PERFORMANCE DURING FATAL ACCIDENTS

4.1 Methodology for Evaluating the Effectiveness of ADAS in FSLDPTs

Through a set of distinct processes and procedures, data concerning fatalities of FSLDPTs was evaluated to determine the effectiveness of ADAS for each of the seven automotive manufacturers. By data mining the NHTSA datasets from the 2016 to 2018 (period where FSLDPTs with ADAS appear in the datasets), trends and correlations about the effectiveness of ADAS technology in FSLDPTs for each brand were established. The process from the data collection through the analysis used in this paper is outlined in Figure 18. Key aspects are explained in the following.

4.1.1 NHTSA Data

Searching for non-proprietary data to evaluate the effectiveness of ADAS technology led to two possible sources, namely, NHTSA and IIHS. Of these, NHTSA provides publicly available data they have collected on fatal accidents dating back to 1975. When a fatal accident occurs, NHTSA sends a data collector to collect state driver licensing files, vehicle registration files, highway department files, crash reports, and vital statistics reports. This data is then used to construct 27 separate files about the accidents (datasets prior to 2014 have fewer files). The combination of these 27 files is known as the Fatal Analysis Reporting System, or FARS. Every entry in FARS is sanitized for personal information prior to public release. This sanitation removes information such as death certificate numbers and other personal identifiers and truncates the Vehicle Identification

Number (VIN) from 17 characters to 12. Each file in FARS links accidents through case numbers. Case numbers begin with the respective U.S State or Territory where the accident occurred, which are identifying digits corresponding to the General Service Administration (GSA) State/Territory codes.

Of the 27 separate csv files in FARS, 4 files – Accident, VINDecoded, Vehicle, Person – were identified as providing pertinent information pertaining to this study. VINDecoded became a FARS file beginning in 2014. For prior years, a function was written to take the truncated VINs and generate a file similar to the FARS VINDecoded file.

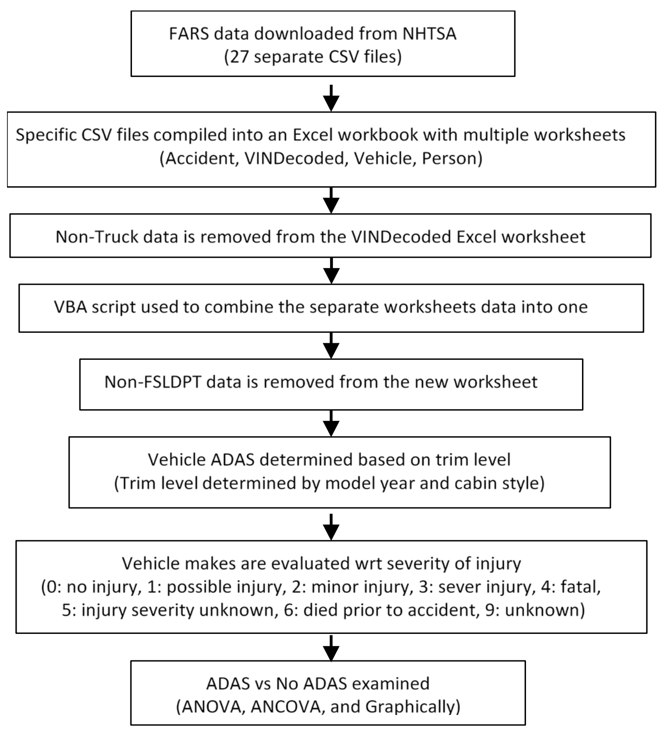

Figure 18. Flow of NHTSA FARS data from collection through evaluation.

Using the four files, VBA scripts were developed and used to link the files and append the data of each accident by linking the case numbers into a new spreadsheet file.

These VBA scripts append the data to create a single file in the order of Person, Vehicle, VINDecoded, and Accident with only the case identifiers (case number, state number, and vehicle number) appearing once per line of data.

The VBA scripts also query the now linked data to only include data from accidents involving FSLDPTs. This query was restricted to only include FSLDPTs that represented a manufacturers' baseline FSLDPT. For example, the RAM 1500 was included while the RAM 2500 and up were excluded. This process was repeated for all seven identified FSDLPTs (Ford F-150, Chevy Silverado, Nissan Titan, Dodge RAM 1500, GMC Sierra, Honda Ridgeline, and the Toyota Tundra).

4.1.2 ADAS Technology Determination in Vehicles

The FARS datasets do not distinguish what ADAS technology (if any) was present in the vehicles. The truncated VINs restricted the ability to simply look up build charts from the manufacturers to determine what ADAS technology was present. Instead, sales brochures (Cheverolet 2014, Ford 2014, GMC 2014, LLC 2014, Nissan 2014, Toyota 2014, Cheverolet 2015, Ford 2015, GMC 2015, LLC 2015, Nissan 2015, Toyota 2015, Cheverolet 2016, Ford 2016, GMC 2016, Honda 2016, LLC 2016, Nissan 2016, Toyota 2016, Cheverolet 2017, Ford 2017, GMC 2017, Honda 2017, LLC 2017, Nissan 2017, Toyota 2017, Cheverolet 2018, Ford 2018, GMC 2018, Honda 2018, LLC 2018, Nissan 2018, Toyota 2018, Cheverolet 2019, Ford 2019, GMC 2019, Honda 2019, LLC 2019, Nissan 2019, Toyota 2019) for each FSLDPT from the last five years (2015 – 2020) were retrieved and examined. This task was conducted by first doing a word search of the sales brochures followed by a full reading of the brochures. This two-stage review was required because some ADAS technologies would appear for a few model years in a row, but then skip a model year and reappear in a subsequent model year. The full reading filled in the inconsistencies, which were caused by spelling errors, name changes, and brand specific branding of technology.

The brochures were then scrutinized to determine what criteria would stratify vehicles based on ADAS availability. This review found that high-end models were likely to have more ADAS technology standard or optional while base model FSLDPTs generally only possessed a few older or legally required ADAS technologies. This precipitated the search for what feature distinguishable from the FARS VINDecoded dataset could be used to stratify the vehicle models. Cabin style and engine size were found to be the best way to stratify the models, and model year was useful in determining which of the high-end models possessed which ADAS technologies.

High-end and low-end models were able to be identified in the FARS datasets by using the information obtained from the auto manufacturer's sales brochures. The high-end models were able to be further delineated into those with ADAS and those without ADAS. Vehicle trim levels where ADAS was optional were excluded from the analysis. This allowed for greater insight into how ADAS affects FSLDPT safety. Low-end models did not possess ADAS technology except for those mandated by law.

4.1.3 Means of Investigation

The data obtained from FARS was analyzed in several manners. The data was initially evaluated to determine how certain factors for a particular year correlated with severity of injury to the FSLDPT occupants and level of damage that the FSLDPT sustained. This was then extended to show how these factors' contribution with respect to severity of injuries and level of damage changed over multiple years.

After stratifying the FSLDPTs as 1) high-end with ADAS, 2) high- end without ADAS, and 3) low-end vehicles, the severity of injury was evaluated for each stratum. Depending on the severity of the impact on the specified individual vehicle, vehicles records could have several occupant injuries attached, but only the most severe vehicle injury was counted for each vehicle in this study.

Vehicle sales data obtained from company 10-K and 20-F reports (mandatory comprehensive reports of publicly traded companies for the Security and Exchange Commission (SEC)) (Barra and III 2015, Fields and Shanks 2015, Groff and Ballinger 2015, Kaczynski 2015, Marchionne and Palmer 2015, Moroe and Kubaru 2015, Barra and III 2016, Fields and Shanks 2016, Groff and Ballinger 2016, Kaczynski 2016, Marchionne and Palmer 2016, Moroe and Kubaru 2016, Barra and III 2017, Groff and Chu 2017, Hackett and Shanks 2017, Kaczynski 2017, Marchionne and Palmer 2017, Moroe and Kubaru 2017, Barra and Suryadevara 2018, Cullum 2018, Groff and Chu 2018, Hackett and Shanks 2018, Manley and Palmer 2018, Moroe and Nakamura 2018) and online web searches (2020) were used for normalizations where necessary.

For both the weather and lighting factors suboptimal/adverse conditions as defined by NHTSA's FARS dataset were combined for separate totals for both respective factors. Adverse weather conditions were a combination of eight different attributes – rain, sleet/hail, freezing rain/drizzle, snow, blowing snow, fog/smoke/smog, severe crosswinds, blowing sand/soil/dirt – as defined by the FARS CRSS Coding and Validation Manual

(NHTSA 2018). Degraded lighting conditions were a combination of initially three different attributes – dark (not lighted), dark (lighted), dark (unknown lighting) based on the FARS CRSS Coding and Validation Manual (NHTSA 2018). This was expanded to include two more lighting conditions – dawn, dusk – forming an extended lighting condition, which was done to see if more of the different brand FSLDPTs would become significant.

Analysis of Variance (ANOVA) tests were conducted to determine the statistical significance of findings. An ANOVA test is a stochastic tool that compares the variances of two or more groups of data. The ANOVA test determines if the datasets are in fact the same datasets or different distinct sets of data. If there is no real difference between the datasets, which is the null hypothesis, the result of the ANOVA P-value (or F-ratio) will be near 1. If there is a significant difference between the datasets, the result of the ANOVA P-value will be less than 0.05. In this research a one-way ANOVA is used with the independent variable used in the test being the Level of Injury. The one-way ANOVA is selected over the two-way ANOVA due to the other possible variable for comparison (Damage Severity) not being independent of Level of Injury. The total numbers of crash involvements, fatalities in the vehicle, and no injuries in the vehicle from 2016 through 2018 were tallied for two bands of vehicle model years (<2015 and ≥2015). The older band of years, while not purposefully being bounded on the minimum year end, did not include any model years prior to the 2000 model year. The bands represent the vehicle model years prior to ADAS and post ADAS. For most auto manufacturers the ADAS introduction vehicle model year is 2015 for FSLDPTs, but Honda introduced ADAS in the 2017 model year for FSLDPTs due to a temporary discontinuation of its FSLDPT offerings. A single factor ANOVA test was performed for the high-end vehicle models comparing the bands for the high-end vehicle models. High-end vehicle models with and without ADAS were selected for the comparison rather than high-end versus low-end as a means to keep as many variable factors such as cabin style or engine size constant. It is also important to note that accidents were not compared between accident years so as to avoid the potential for laws changing between accident occurrences. If there is a statistical difference (P-value < 0.05), then the comparison of ADAS to non-ADAS vehicles would indicate there was either an improvement or depreciation in the survivability of the FSLDPT.

4.2 Results for the Full-Size Light-Duty Pickup Truck Sector

By evaluating several makes and models involved in accidents from 2015 to 2018, a portrait of the effectiveness of ADAS technology at reducing the severity of injuries from accidents has been developed. The additional observation of how adverse conditions affect accidents lead to a determination for how ADAS equipped FSLDPTs are preforming relative to their non-ADAS counterparts in less than ideal conditions. The Ford F-150, Chevrolet Silverado, GMC Sierra, RAM 1500, Toyota Tundra, Nissan Titan, and Honda Ridgeline were the FSLDPTs identified for the comparison in this study.

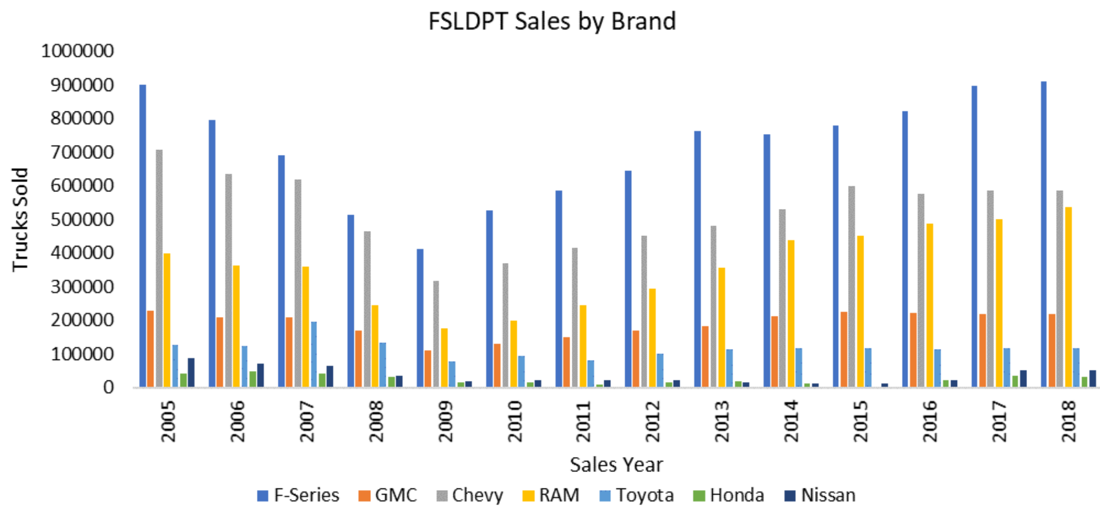

Figure 19. FSLDPT sales data by brand from 2005 to 2018.

4.2.1 Initial Analysis of Factors of Interest

From the NHTSA FARS data, ten factors of interest were identified for accidents, including: 1) vehicle number for accident involvement, 2) harmful event type, 3) injured occupant seat position, 4) injured occupant's age, 5) injured occupant's sex, 6) accident geographic location, 7) driver's alcohol consumption, 8) drug use, 9) vehicle impact location, and 10) model year. These accidents factors were correlated against the severity of injuries in the accident, which ranges on a scale from 0 to 4 with 0 being no injury and 4 being fatal injury (NHTSA 2018). Three additional values outside the scale, (i.e., 5, 6, 9) are used to denote "uncertainty in severity" (5), "unrelated death" (6), or "unknown" (9). The ten aforementioned factors were also correlated to the level of vehicle damage ranging on a scale of 0 to 6 with 0 being "no damage" and 6 being "disabling damage". Vehicle damage values of 8 and 9 are also used by NHTSA and denote "not reported" and "unknown", respectively.

During the initial analysis, it was found that the majority of fatalities and serious injuries occurred when the vehicle damage sustained was level 6 - disabling. Several other factors behaved as expected, such as most injuries occurring in the primary vehicle in the accident and the occupant of the driver's seat sustaining the most injuries of all types. These were expected because only one vehicle is necessary for an accident to occur. Also, if there is one occupant of the vehicle then the most common seat position of the vehicle occupant is the driver's seat. The most common harmful event type was collision of vehicles in motion.

Accidents are defined by harmful events. NHTSA identifies 56 different harmful events possible for an accident. Of the 56 possible harmful events, four were common to FSLDPT accidents – roll over, motor vehicle in transport, pedestrian, and tree – with motor vehicle in transport as the most frequent. Motor vehicle in transport means that the accident occurred from vehicles driving on the road experiencing a collision.

4.2.2 ADAS Effectiveness for Different FSLDPTs.

In the section ADAS Technology Determination in Vehicles, high-end and low-end models were able to be stratified using the FARS datasets by using the information obtained from the auto manufacturer's sales brochures. The high-end models were further delineated into those that possessed ADAS and those that did not poses ADAS. Low-end models in most cases did not possess ADAS technology except when a technology was mandated by law. Table 7 delineates the information about the high-end FSLDPTs between those with ADAS and those without ADAS for the different injuries sustained during accidents in 2018. The RAM 1500 consistently has much lower injury counts across all injury severities for high-end FSLDPTs without ADAS than for its FSLDPTs with ADAS. During RAM's transition to incorporating ADAS in their FSLDPTs the company changed ownership from Dodge to Chrysler Fiat. The change in ownership appears in conjunction with the large disparity in quantity of injuries. There may be other differences in the vehicle between RAM owned by Dodge and RAM owned by Chrysler Fiat that this study does not explore. The other vehicle model FSLDPTs did not change owner ship; however, the Honda Ridgeline was discontinued in 2015 and brought back with ADAS in 2017. When looking at the totals for each FSLDPT, there are considerable differences in sales between the seven FSLDPTs. Ford sold nearly a million FSLDPTs in 2018 with Chevrolet and RAM having each sold about half as many and GMC about a quarter of the total FSLDPTs sold by Ford, respectively. The remaining three FSLDPT models from Honda, Toyota and Ram combined sold less than the number of GMC FSLDPTs. Rather than talk about accident numbers in Table 7 as normalized by the number of vehicles of each model at corresponding vehicle trim level still on the road or sold as to do a comparison between automotive manufacturers, whole numbers are provided. The number of the High-end models both with and without ADAS involved in fatal accidents are small, but that is a factor of there being approximately 40,000 vehicles total involved in fatal accidents for the approximately 240 million registered vehicles in the United States. This study is only looking at the high-end models of FSLDPTs which make up a small portion of the FSLDPTs sold each year further reducing the likelihood for large vehicle numbers. The values of vehicles sold by each automotive manufacturer are depicted in Figure 19.

Table 7. Table of high-end ADAS and non ADAS injuries in the 2018 FARS data for each of the seven FSLDPTs.

Make & Model	Injury Level	ADAS	High w/o	Difference (%)	Make & Model	Injury Level	ADAS	High w/o	Difference (%)
CHEVY Silverado	0	55	68	19%	HONDA Ridgeline	0	0	2	100%
	1	24	23	-4%		1	0	3	100%
	2	27	25	-8%		2	1	1	0%
	3	15	27	44%		3	1	1	0%
	4	28	50	44%		4	0	6	100%
GMC Sierra	0	15	11	-36%	NISSAN Titan	0	10	19	47%
	1	6	4	-50%		1	5	3	-67%
	2	12	3	-300%		2	9	5	-80%
	3	1	0	-		3	10	4	-150%
	4	5	1	-400%		4	13	10	-30%
RAM 1500	0	186	9	-1967%	FORD F-150	0	40	102	61%
	1	51	3	-1600%		1	12	24	50%
	2	65	3	-2067%		2	17	35	51%
	3	37	3	-1133%		3	3	27	89%
	4	84	3	-2700%		4	13	184	93%
TOYOTA Tundra	0	1	14	93%					
	1	0	5	100%					
	2	0	2	100%					
	3	2	1	-100%					
	4	2	2	0%					

4.2.3 ANOVA Testing of ADAS Effectiveness.

The FARS database is intended for use in reporting of fatal accidents, but it also includes data concerning less severe injuries that occurred during fatal accidents. While this does not lessen the severity of the accidents it does provide an interesting insight to how well the vehicle preformed at protecting its occupant during such a severe accident. The ANOVA test results for all the FSLDPT models are listed in Table 8. Three ANOVA tests were conducted for each of the seven FSLDPT models for the different injury severities from 2016 to 2018. For reducing fatal injuries, the Ford F150 and Chevrolet Silverado were statistically significant. The RAM 1500 was also statistically significant, but as show in Table 7, statistically significance was detrimental rather than advantageous with more fatalities occurring in the ADAS equipped vehicles. This trend of the RAM 1500 being statistically significant in a detrimental manner continued for the other three ANOVA tests.

For reducing all injuries, the Ford F-150, the Chevrolet Silverado, and the Toyota Tundra were statistically significant. The all injuries analysis includes the fatal injury and the no injury totals. From reviewing the totals, the fatality reduction for Chevrolet and the no injury reduction for Toyota is what drove the statistical significance for the all injuries analysis for those two FSLDPT models. The Ford F-150 had fewer injuries for all individual injury severities.

For the occurrence of no injuries the Ford F-150 and the Toyota Tundra were statistically significant. For the no injury severity totals, both the F-150 and the Tundra had fewer instances with ADAS equipped vehicles than with unequipped vehicles. While intuitively this seems in opposition to the desired outcome, it in fact is advantageous. The all injury analysis, which includes both no injuries and fatal injuries, improved for these FSLDPT models, and in the F-150's case there was improvement with respect to fatal injuries. Holistically these results show there were fewer accidents with the ADAS equipped FSLDPTs contributing to the lower totals for no injuries. With that said, it is important to remember the limitations of this work as described in section 1.5 Assumptions, newer vehicles tend to more crashworthy than older vehicles, older vehicles tend to be driven by drivers in a more haphazard manner than newer vehicles, and the type of person driving an older vehicle tends to be driven by a different demographic of personalities than newer vehicles. All of which can affect the propensity to be involved in a crash.

Table 8. Table of ANOVA results for comparing FSLDPTs sustained injury levels with and without ADAS among the different auto manufacturers' vehicle models.

Vehicle Make and Model	Injury Level	P-Value	Significance
Ford F-150	No Injury	0.0409	Significant
	All Injuries	0.0029	Significant
	Fatal Injuries	0.0131	Significant
Chevrolet Silverado	No Injury	0.3859	Not Significant
	All Injuries	0.0228	Significant
	Fatal Injuries	0.0020	Significant
GMC Sierra	No Injury	0.4917	Not Significant
	All Injuries	0.9701	Not Significant
	Fatal Injuries	0.3301	Not Significant
RAM 1500	No Injury	0.0118	Significant
	All Injuries	0.0017	Significant
	Fatal Injuries	0.0018	Significant
Toyota Tundra	No Injury	0.0044	Significant
	All Injuries	0.0022	Significant
	Fatal Injuries	0.1401	Not Significant
Honda Ridgeline	No Injury	0.2857	Not Significant
	All Injuries	0.1521	Not Significant
	Fatal Injuries	0.1194	Not Significant
Nissan Titan	No Injury	0.4346	Not Significant
	All Injuries	0.9527	Not Significant
	Fatal Injuries	0.8197	Not Significant

4.2.4 ADAS Effectiveness in Adverse Driving Conditions for Different FSLDPTs

As previously stated in ADAS Technology Determination in Vehicles, high-end and low-end models were able to be stratified in the FARS datasets using the information obtained from the auto manufacturer's sales brochures. The high-end models were further delineated into those that possessed ADAS and those that did not poses ADAS. Low-end models in most cases did not possess ADAS technology except when a technology was mandated by law, which at present is limited to rear backup cameras. Table 9 delineates the information about the high-end FSLDPTs between those with ADAS and those without ADAS for the different injury levels sustained during accidents from 2016 to 2018 for the five cases of mitigating conditions – weather, drinking, drugs, and lighting.

The RAM 1500 consistently has much lower injury counts across all injury severities under adverse conditions for high-end RAM 1500s without ADAS than RAM 1500s with ADAS as shown in Table 7. Even though, the values for the adverse conditions are low an ANOVA test is still reasonable because the number of groups being compared is two and the sampling points are the five injury levels. If there are more sample points than groups, which there are, it is reasonable to perform an ANOVA test. During RAM's transition to incorporating ADAS in their FSLDPTs the company changed ownership from Dodge to Chrysler Fiat. The change in ownership appears to account for the large disparity in quantity of injuries. There may be differences in vehicle quality between RAM owned by Dodge versus RAM owned by Chrysler Fiat which this study cannot take into account. One of such changes is the standardizing of placing ADAS in all RAM 1500s regardless of trim level, which also drove the total number up. None of the other vehicle models changed owner ship, but the Honda Ridgeline was discontinued in 2015 and brought back with ADAS in 2017. The discontinuation of the Honda Ridgeline causes their total number of accidents across all five adverse conditions. This adds a level of obscurity to whether there is real significance for results of the RAM 1500 and Honda Ridgeline.

When looking at the totals for each FSLDPT, there are considerable differences in sales between the seven FSLDPTs. Ford sold nearly a million FSLDPTs in 2018 with Chevrolet and RAM having each sold about half as many and GMC sold approximately a quarter of the total FSLDPTs as Ford, respectively. The remaining three FSLDPT models combined sold below the number of GMC FSLDPTs as shown in Figure 19. When looking at Table 9 it is important to not look at the tallies of each level of injury for the adverse conditions and think that the fewer injuries represent one FSLDPT being inherently safer than another FSLDPT of a different brand. The FARS database is intended for use in reporting of fatal accidents, but it also includes data concerning less severe injuries that occurred during fatal accidents. While this does not lessen the severity of the accidents it does provide an interesting insight to how well the vehicle preformed at protecting its occupant during such a severe accident. A number of studies indicated how ADAS, while its' main purpose is crash avoidance, also acts to reduce injury in cases when crashes occur (Eichelberger and McCartt 2014, Fildes, Keall et al. 2015, Christopher Wiacek 2017, Cicchino 2017, Cicchino 2018).

Table 9. Table of high-end ADAS and non ADAS injury totals under adverse conditions from 2016 to 2018 FARS data for each of the seven FSLDPTs.

		Weather		*Drinking*		*Drugs*		*Lighting*		*Lighting Expanded*	
Make & Model	Injury Level	ADAS	High w/o	ADAS	High w/o	ADAS	High w/o	ADAS	High w/o	ADAS	High w/o
FORD F-150	0	3	1	2	5	0	2	20	25	20	25
	1	0	0	0	3	0	4	1	4	1	4
	2	3	0	0	3	0	1	9	3	9	3
	3	0	0	1	3	0	0	6	5	6	5
	4	2	2	4	11	1	3	8	13	8	13
CHEVROLET Silverado	0	19	28	5	12	0	1	49	95	58	104
	1	9	8	3	3	0	2	19	22	20	24
	2	5	11	7	7	2	1	16	30	16	36
	3	4	9	3	14	2	2	10	39	12	40
	4	6	17	13	33	6	13	26	84	27	92
GMC Sierra	0	2	1	1	2	0	0	17	11	18	11
	1	1	3	0	0	0	0	1	1	1	1
	2	1	0	1	3	0	0	5	6	8	6
	3	1	1	1	1	2	0	4	1	4	1
	4	1	1	0	0	0	1	5	7	6	7
RAM 1500	0	27	2	15	1	5	1	171	10	187	10
	1	24	0	12	0	4	0	46	2	51	2
	2	23	0	12	0	7	0	57	2	61	2
	3	20	0	11	0	2	0	48	2	52	2
	4	31	0	33	0	12	0	101	2	106	2
TOYOTA Tundra	0	0	7	0	6	0	0	2	10	2	10
	1	0	1	1	0	0	0	2	5	2	5
	2	0	1	0	1	0	1	0	2	0	2
	3	0	1	0	1	0	1	2	2	2	2
	4	0	4	0	2	0	0	1	5	1	5
HONDA Ridgeline	0	1	0	1	0	0	0	0	3	0	4
	1	0	1	0	0	0	0	0	2	0	3
	2	0	2	0	0	0	0	0	1	0	2
	3	0	0	0	0	0	0	1	1	1	1
	4	0	4	0	0	0	2	0	3	0	4
NISSAN Titan	0	1	4	0	2	0	1	7	8	7	10
	1	0	2	0	2	0	0	0	3	0	3
	2	2	4	1	1	0	1	5	2	5	3
	3	1	0	1	0	1	0	8	0	8	0

	4	2	5	0	2	1	1	5	4	6	4

4.2.5 ANOVA Testing of ADAS Effectiveness During Adverse Conditions

Five ANOVA tests were conducted for each of the seven FSLDPT models for the different mitigating conditions from 2016 to 2018. The ANOVA tests were conducted to see if first vehicles with ADAS levels of injuries during adverse conditions can be considered as a part of the same or different groups as those FSLDPTs without ADAS, which is displayed in Table 10. For this test a desirable outcome is there being a statistical difference between groups, which is a P-value <0.05. Then, ANOVA tests were conducted to determine if there were differences in the groups of ADAS level of injury when there were adverse conditions as opposed to when adverse conditions were not present. This is shown in Table 11, where now a desirable outcome is there not being a statistical difference between groups, or in P-value results a value >0.05 is desirable. Some of the smaller sample sizes may have led to false non-significant results.

Table 10. Table of ANOVA results for comparing FSLDPTs sustained injury levels with and without ADAS among the different auto manufacturers' FSLDPT models with various adverse conditions present. Here statistical significance is desirable, meaning that there is a difference between ADAS and non-ADAS performance.

Vehicle Make and Model	*Adverse Condition*	*P-Value*	*Significance*
Ford F-150	Weather	0.240	Not Significant
	Drinking	0.070	Not Significant
	Drugs	0.040	Significant
	Lighting	0.823	Not Significant
	Lighting Extended	0.823	Not Significant
Chevrolet Silverado	Weather	0.228	Not Significant
	Drinking	0.204	Not Significant
	Drugs	0.501	Not Significant
	Lighting	0.103	Not Significant
	Lighting Extended	0.110	Not Significant
GMC Sierra	Weather	1.000	Not Significant
	Drinking	0.371	Not Significant

	Drugs	0.667	Not Significant
	Lighting	0.729	Not Significant
	Lighting Extended	0.543	Not Significant
RAM 1500	Weather	<0.001	Significant
	Drinking	0.004	Significant
	Drugs	0.010	Significant
	Lighting	0.009	Significant
	Lighting Extended	0.010	Significant
Toyota Tundra	Weather	0.048	Significant
	Drinking	0.130	Not Significant
	Drugs	0.141	Not Significant
	Lighting	0.055	Not Significant
	Lighting Extended	0.055	Not Significant
Honda Ridgeline	Weather	0.160	Not Significant
	Drinking	0.347	Not Significant
	Drugs	0.347	Not Significant
	Lighting	0.006	Significant
	Lighting Extended	0.003	Significant
Nissan Titan	Weather	0.100	Not Significant
	Drinking	0.066	Not Significant
	Drugs	0.580	Not Significant
	Lighting	0.427	Not Significant
	Lighting Extended	0.593	Not Significant

From Table 10 the Ford F-150, RAM 1500, Toyota Tundra, and Honda Ridgeline indicate some level of statistical significance meaning there exists a difference between their respective FSLDPTs with ADAS and those without ADAS. This is generally desirable with the RAM 1500 being an exception for the reasons previously stated about their ADAS equipped FSLDPTs having an increase in total accident numbers. Honda had uneven comparison because in 2016 their FSLDPTs were still on the road from prior to the FSLDPT being discontinued before being reintroduced in 2017. For this reason, the significance of Honda should not be viewed as a certainty. With that in mind the Ford F-150 and Toyota Tundra showed statistical improvement for when the adverse conditions of drugs present in the driver's system and poor weather, respectively. The statistical improvement for the Ford F-150 when the driver had drugs in their system indicates that the ADAS technology is potentially giving the driver ample time to make corrections or the ADAS is driving the vehicle to avoid the danger itself. This is supported by the Ford drinking adverse condition being almost statistically significant as well. The performance of ADAS is interesting when looking at the results of Table 11, where the desirable outcome is no significance. Even though Ford and Toyota FSLDPTs with ADAS performed better than non-ADAS versions during adverse conditions, the ADAS systems performed differently between adverse and non-adverse conditions of drug use and weather, respectively. What was a major positive outcome from Table 11 was how during the adverse condition of lighting extended, meaning it is dark out and the lighting is not better than that at dusk or dawn, for all but the Nissan Titan did not affect ADAS performance. This is an improvement over the findings of (Cicchino and Zuby 2017, A. Sumi 2019, Spicer, Vahabaghaie et al. 2021), which found there to be a deprecation in the performance of ADAS during poor lighting conditions. It was also encouraging to see the ADAS performance of the Ford F-150 and the Nissan Titan were not affected by adverse weather conditions. Poor weather conditions pose issues for ADAS sensors as light and audio sensors can be distorted due to refraction and absorption during precipitation.

4.2.6 Result Synopsis

With the ever more availability of ADAS technology in FSLDPTs, the increased use of ADAS and overall truck design has shown the potential to improve the survivability for truck occupants during an accident. There is a need for several FSLDPT manufacturers to reassess their ADAS technologies to be on par with those found in Ford's F-150 and Chevrolet's Silverado as detailed in Table 8 and discussed in the section ANOVA Testing of ADAS Effectiveness. At present, according to the results, GMC, Honda, Nissan, and RAM FSLDPTs fall behind Toyota, Chevrolet, and especially Ford in their ability to prevent accidents and reduce injury severity. Of the 18% of registered vehicles, slightly more than half show improvement in reduction of injuries and fatalities. The lack of improvement by GMC, Honda, Nissan, and RAM in any of the injury categories should not be classified as a failure of safety features. Rather, the ADAS technology in these FSLDPTs are better classified as features of convenience. These convenience features may help prevent accidents not encompassed by the FARS data used in this analysis. It is interesting that Chevrolet would show improvement while GMC did not. Both companies are subsidiaries of General Motors and likely have similar vendors for ADAS sensors. When talking about ADAS as a convenience certain ADAS technologies more readily fall into that category based on what they are meant to achieve and the type of accident they supposed to prevent. These are generally seen as low speed impacts where damage is cosmetic. The data used in this study would not reveal how important these ADAS technologies of convenience are at preventing damage. The fact that several brands did not show statistical improvement from the NHTSA data is potentially concerning as the ADAS technologies meant for safety should show their worth from this data, but this may just be an effect of sample sizes being small. As mentioned, General Motors owns two of the seven brands reviewed in this study and they should behave similarly. GMC actually performed worse with ADAS in 2018 than without ADAS that year. This points to an unseen factor effecting GMC FSLDPTs such as how they are positioned on the vehicle. With respect to the other brands that did not improve, they may be in a similar situation to GMC or their ADAS technologies may not be on par with those of that showed improvement. This is detailed in greater depth in (Fish and Bras 2021).

Table 11. Table of ANOVA results for comparing FSLDPTs sustained injury levels with ADAS among the different auto manufacturers' FSLDPT models with various adverse

conditions present or absent. Here statistical significance is undesirable, meaning that there is no difference between ADAS performance under adverse conditions and preferred conditions.

Vehicle Make and Model	*Adverse Condition*	*P-Value*	*Significance*
Ford F-150	Weather	0.389	Not Significant
	Drinking	0.021	Significant
	Drugs	0.018	Significant
	Lighting Extended	0.079	Not Significant
Chevrolet Silverado	Weather	0.017	Significant
	Drinking	0.021	Significant
	Drugs	0.012	Significant
	Lighting Extended	0.240	Not Significant
GMC Sierra	Weather	0.046	Significant
	Drinking	0.035	Significant
	Drugs	0.039	Significant
	Lighting Extended	0.762	Not Significant
RAM 1500	Weather	0.014	Significant
	Drinking	0.009	Significant
	Drugs	0.005	Significant
	Lighting Extended	0.583	Not Significant
Toyota Tundra	Weather	<0.001	Significant
	Drinking	0.002	Significant
	Drugs	<0.001	Significant
	Lighting Extended	1.000	Not Significant
Honda Ridgeline	Weather	0.242	Not Significant
	Drinking	0.195	Not Significant
	Drugs	0.065	Not Significant
	Lighting Extended	0.681	Not Significant
Nissan Titan	Weather	0.132	Not Significant
	Drinking	<0.001	Significant
	Drugs	<0.001	Significant
	Lighting Extended	0.023	Significant

Only two FSLDPTs, the Ford F-150 and the Toyota Tundra, clearly demonstrated improvement in injury level reduction in ADAS equipped FSLDPTs over FSLDPTs without ADAS for the adverse conditions drug use and poor weather, respectively. A third FSLDPT, the Honda Ridgeline, potentially showed improvement of ADAS over non-ADAS for injury level reduction during an adverse condition of poor lighting, but due to the discontinuation and reintroduction of the Honda Ridgeline skepticism of the significance exists. A positive sign was how all FSLDPTs with ADAS had at least one adverse condition where the ADAS statistically performed the same regardless of the presence or absence of the adverse condition. The most common being the same performance during poor lighting conditions. The Nissan Titan was an exception, but it performed the same during poor weather conditions. The Ford F-150 and Honda Ridgeline also performed the same regardless of the presence or absence of poor weather conditions in addition to the lighting conditions. These consistent performances of ADAS equipped FSLDPTs regardless of the presence or absence of adverse conditions is an improvement that had been anticipated, but not previously proven by (A. Sumi 2019). This indicates that the ADAS sensors are refined enough to compensate for environmental adverse conditions. This does not mean that these ADAS packages are perfect and these are the best results ADAS can achieve. It simply means that the combination of sensors and technologies used for these vehicles compensate for deficiencies of any individual ADAS sensor/technology.

4.3 A Look at the Industry Leader (Ford F-150)

4.3.1 Means of Investigation

The data obtained from FARS was analyzed in several manners. The data was initially evaluated to determine how certain factors for a particular year correlated with severity of injury to the FSLDPT occupants and level of damage that the FSLDPT sustained. This was then extended to show how these factors' contribution with respect to severity of injuries and level of damage changed over multiple years.

After stratifying the FSLDPTs as 1) high-end with ADAS, 2) high- end without ADAS, and 3) low-end vehicles, the severity of injury was evaluated for each stratum. Depending on the severity of the accident, vehicles records could have several occupant injuries attached, but only the most severe vehicle injury was counted for each vehicle in this study. Table 12 delineates the information about the high-end and low-end vehicles found in 2018. The percentage of the 1,043 accidents involving F-150s that had ADAS represents 2.3% to 2.6% of the accidents. The range is dependent on the inclusion or exclusion of F-150 XLT trims which may or may not have ADAS depending on their option package. To ensure a clear ADAS vs non-ADAS comparison, vehicles like the XLTs were excluded if it was not clear whether they a) belonged to the low-end and truly were without ADAS or b) were mid-level vehicles with options for ADAS, but it could not be discerned if ADAS was present or not. In total, 193 vehicles were excluded from the 1,034 vehicle accidents because of ambiguity in ADAS presence (see Table 12).

Vehicle sales data obtained from company 10-K reports (mandatory comprehensive reports of publicly traded companies for the Security and Exchange Commission (SEC)) (Fields and Shanks 2015, Fields and Shanks 2016, Hackett and Shanks 2017, Hackett and Shanks 2018) and online web searches (2020) were used for normalizations where necessary.

ANOVA tests were conducted to determine the statistical significance of findings. The total numbers of accidents, fatalities, and no injuries from 2016 through 2018 were tallied for three bands of vehicle model years (<2009, 2009-2014, and ≥2015). The three bands represent three generations for Ford F-150s. The prior to 2009 band (<2009) represents a vehicle model before a major vehicle redesign. The 2009 to 2014 was the band of the new vehicle design before ADAS was introduced to the vehicles. The 2015 and later high-end vehicle models have the same new vehicle design with the addition of ADAS.

A single factor ANOVA test was performed for the high-end vehicle models comparing the three bands of model years (<2009, 2009-2014, >2014) in four ways (see also 11): 1) the first two bands, 2) the latter two bands, 3) the first two bands combined verses the final band, and 4) all three bands. These ANOVA tests showed how the new vehicle model design without ADAS compared to the older vehicle model design without ADAS (per comparison 1); how ADAS compared to non-ADAS for the same vehicle model design (per comparison 2); how ADAS compared to non-ADAS regardless of vehicle model design (per comparison 3), and how ADAS compared to non-ADAS accounting of vehicle model design (per comparison 4).

Table 12. Table of high-end and low-end accidents in the 2018 FARS data, and the adjusted percentages for normalizing vehicles sold. The total population of F-150s involved in accidents in 2018 was 1,043 per FARS data of which 850 were used for ADAS fatality comparison.

	High-end vehicles			Low-end vehicles		
Vehicles in accidents (Total = 1,043 of which 850 were included in the study)	384	36.8% of accidents		466	44.7% of accidents	
Vehicles having a fatality (Accidents = 383)	127	12.2% of accidents	33.1% of High-end Vehicle Accidents	256	24.5% of accidents	54.9% of Low-end Vehicle Accidents
Vehicles having a fatality with ADAS features standard (High-end 2015+)	25	2.4% of accidents	6.5% of High-end Vehicle Accidents	N/A	N/A	N/A

It is expected that vehicles with ADAS will be statistically different than those without ADAS. The different vehicle model designs could contribute to a statistical difference between vehicles with and without ADAS. Thus, the new vehicle model design without ADAS is compared to the old vehicle model design without ADAS. If there is a statistical difference (P-value < 0.05), then the comparison of ADAS to non-ADAS vehicles would need to be limited to only the new vehicle model design. If there is not a statistical difference, it is permissible to compare ADAS to all non-ADAS regardless of vehicle model design. No or weak statistical difference in vehicle model design is also possible, in which case, ADAS can be compared to all non-ADAS vehicles regardless of vehicle model design.

4.3.2 Results of Studying the Industry Leader

By evaluating several makes and models involved in accidents from 2015 to 2018, a portrait of the effectiveness of ADAS technology at reducing the severity of injuries from accidents has been developed. Here the Ford F-150 is specifically used as it represents on average, the most widely registered FSLDPT in the US (Miller 2019).

4.3.2.1 Initial Analysis of Factors of Interest

From the NHTSA FARS data, ten factors of interest were identified for accidents, including: 1) vehicle number for accident involvement, 2) harmful event type, 3) injured occupant seat position, 4) injured occupant's age, 5) injured occupant's sex, 6) accident geographic location, 7) driver's alcohol consumption, 8) drug use, 9) vehicle impact location, and 10) model year. These accidents factors were correlated against the severity of injuries in the accident, which ranges on a scale from 0 to 4 with 0 being no injury and 4 being fatal injury (NHTSA 2018). The FARS database is intended for use in reporting of fatal accidents, but it also includes data concerning less severe injuries that occurred during fatal accidents. While this does not lessen the severity of the accidents it does provide an interesting insight to how well the vehicle preformed at protecting its occupant during such a severe accident. Three additional values outside the scale, (i.e., 5, 6, 9) are used to denote "uncertainty in severity" (5), "unrelated death" (6), or "unknown" (9). The ten aforementioned factors were also correlated to the level of vehicle damage ranging on a scale of 0 to 6 with 0 being “no damage” and 6 being “disabling damage”. Vehicle damage values of 8 and 9 are also used by NHTSA and denote “not reported” and “unknown”, respectively.

During the initial analysis, it was found that the majority of fatalities and serious injuries occurred when the vehicle damage sustained was level 6 - disabling. Several other factors behaved as expected, such as most injuries occurring in the primary vehicle in the accident and the occupant of the driver’s seat sustaining the most injuries of all types. These were expected because only one vehicle is necessary for an accident to occur. Also, if there is one occupant of the vehicle then the most common seat position of the vehicle occupant is the driver’s seat. The most common harmful event type was collision of vehicles in motion.

4.3.2.2 Injury Severity for Bands of Model Year

Accidents are defined by harmful events. NHTSA identifies 56 different harmful events possible for an accident. Of the 56 possible harmful events, four were common to FSLDPT accidents – roll over, motor vehicle in transport, pedestrian, and tree – with motor vehicle in transport as the most frequent. Motor vehicle in transport means that the accident occurred from vehicles driving on the road experiencing a collision with another vehicle.

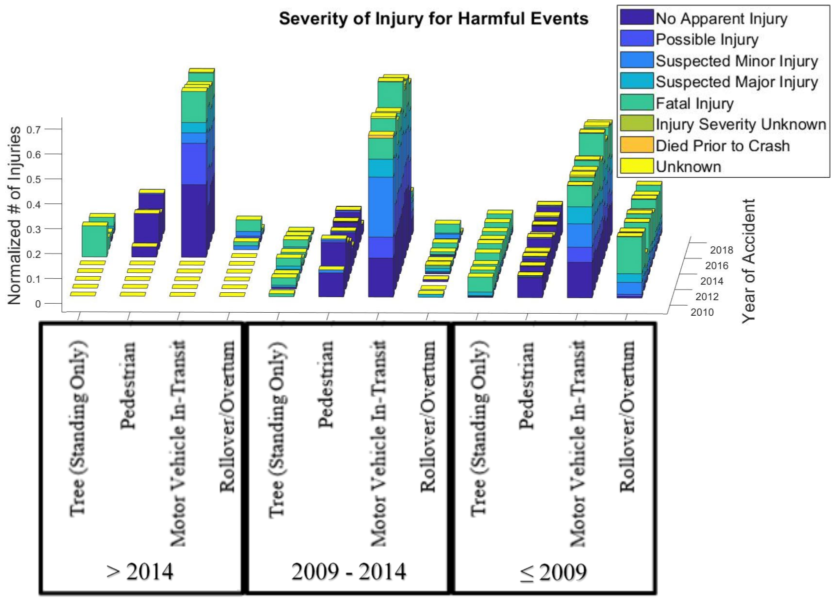

Figure 20. Relation between harmful events and injury severity normalized over sales and distributed over three bands of model years: older than 2009, 2009 to 2014, and newer than 2014.

Figure 20 illustrates a shift of severity of injury for three time periods of F-150 models where the majority of injuries moves from fatal injuries in vehicles older than 2009 to minor injury in 2009-2014 vehicles to no injury in vehicles newer than 2014. Newer models experienced a greater percentage of their total accident injuries as low severity injuries (no injury, possible injury, and minor injury), when normalized for total accidents, than older models during accidents involving a fatality. Figure 20 indicates that ADAS is improving the safety of occupants during accidents and reducing the occurrence of accidents. The adoption of ADAS should be disseminated to all FSLDPT model levels.

4.3.2.3 ANOVA Results for Testing of ADAS Effectiveness

The ANOVA test between fatalities occurring in high-end and low-end models found a weak statistical significance, P-value 0.063, for models newer than 2014. This matched with an ANOVA test between accidents occurring in high-end and low-end models, P-value 0.06. There was also statistical significance between non-ADAS and ADAS for fatalities. Statistical significance was found for accidents with no injuries between non-ADAS and ADAS equipped FSLDPTs. As ADAS technology improves and becomes more standardized the safety of the FSLDPT occupants improves.

As shown in Table 13, there was weak statistical significance for high-end vehicle models when comparing the 2009-2014 and the >2014 band. A weak statistical significance was also found for the <2009 and 2009-2014 bands. There was little to no change in significance for injuries of occupants between the old vehicle model design (<2009) and the new vehicle model design prior to ADAS (2009 – 2014). There was a weak change in significance between the new vehicle model design pre (2009 – 2014) and post ADAS (>2014); however, when comparing ADAS (>2014) to all non-ADAS (≤2014) there was a significant change for injuries of occupants. When comparing the three vehicle model year bands there was only a significant change for fatal injuries.

Taking these results together indicates that ADAS has made a significant change in reducing the severity of injuries of FSLDPT occupants. This finding is reinforced by plotting the 2018 severity of injuries of the different F-150 models, as shown in Figure 21. As shown in Figure 21, high-end F-150s with ADAS have roughly 4 times fewer fatalities than high-end FSLDPTs without ADAS and 10 times fewer fatalities than low-end FSLDPTs.

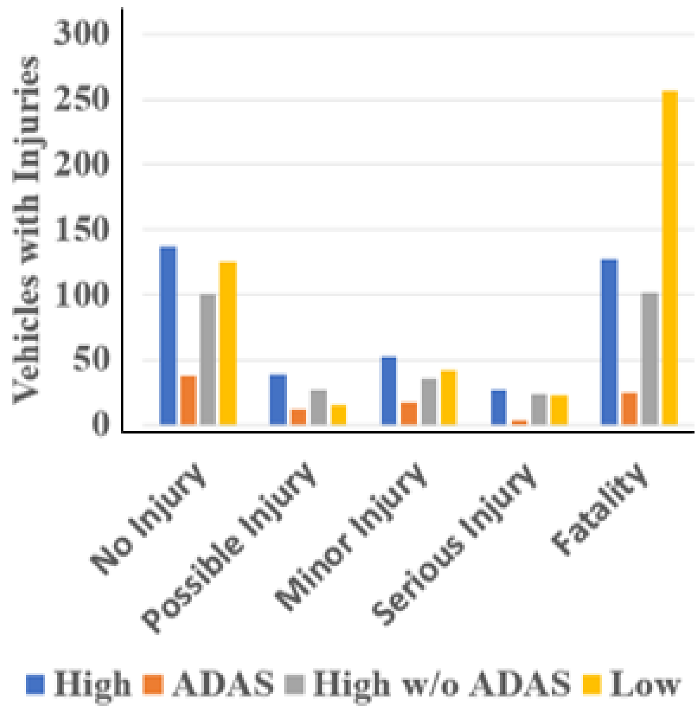

Figure 21. Severity of injuries by high-end (High), high-end with ADAS (ADAS), high-end without ADAS, and low-end (Low) FSLDPTs for 2018.

4.3.2.4 ANOVA and ANCOVA Analysis of Factors Affecting Industry Leader ADAS

When vehicles with ADAS were in accidents, further ANOVAs were conducted to determine what factors affected the level of injury in FSLDPTs with ADAS. Factors that were statistically significant were the US State where the accident occurred (P=0.044), the type of harmful event (P<0.001), the road being a rural road or an urban road (P<0.001), the trafficway's division (P=0.036), and road surface conditions (P=0.004). Interestingly, age or sex were not statistically significant even with approximately three out of four drivers being male. This is important as age and gender are both used for calculating insurance premiums. Since neither affects ADAS performance, insurance companies should remove those factors for calculating premiums when the FSLDPT has ADAS. With that said insurance premiums are regulated at the state level and is associated with risk tendencies irregardless of what vehicle is being driven.

Table 13. ANOVA results for comparison of model year bands (<2009, 2009-2014, >2014) for high-end vehicles

Accident Injury	Vehicle Model Year Bands Being Compared	P-value	Significance
Fatal Injury	<2009 & 2009-2014 vs >2014	0.0131	Significant
	2009-2014 vs >2014	0.137	Very Weak Significance
	<2009 vs 2009-2014	0.0907	Weak Significance
	<2009 vs 2009-2014 vs >2014	0.0168	Significant
All Injury Types	<2009 & 2009-2014 vs >2014	0.0029	Strong Significance
	2009-2014 vs >2014	0.108	Very Weak Significance
	<2009 vs 2009-2014	0.9247	Not Significant
	<2009 vs 2009-2014 vs >2014	0.0874	Weak Significance
No Injury	<2009 & 2009-2014 vs >2014	0.0409	Significant
	2009-2014 vs >2014	0.0961	Weak Significance
	<2009 vs 2009-2014	0.7226	Not Significant
	<2009 vs 2009-2014 vs >2014	0.1252	Very Weak Significance

Rural versus urban fatal accidents for FSLDPTs ratio is approximately 2:1 for ADAS equipped and non-ADAS FSLDPTs which is consistent with the IIHS press release on the matter (Institute 2019). The state factor seemed to be describable with the rural or urban road factor matching a NHTSA fact sheet (NHTSA 2019). It was found from ANCOVA testing that the function of the trafficway, vehicle travel speed, road curvature, number of lanes, road profile, pavement type, and excessiveness of speed were not statistically significant when used as a covariable with the rural or urban factor. A summary of the ANCOVA testing is depicted in Table 14.

Table 14. Statistical significance for ANOVA of rural vs urban and ANCOVA for other factors (underlined values are significant).

Factors		Rural/ Urban
ANOVA		0.0003
Covariant for ANCOVA	Route	0.6092
	Function System	0.3614
	Travel Speed	0.7987
	Speed Limit	0.0299
	Number of Lanes	0.1537
	Traffic Way	0.4573
	Road Profile	0.5544
	Pavement Type	0.2315
	Surface Conditions	0.9896

Speed limit used as a covariable with rural or urban was statistically significant from ANCOVA testing with a P-value of 0.030 when unknowns and non-trafficways were excluded. This is intriguing because the factors involving the FSLDPTs' speed from ANOVA and ANCOVA testing were not statistically significant. The FARS data does not include the traffic density on the road during the accident. Traffic density is accounted for when planning roadway speed limits, since the higher speed limits of rural roads indicate a lower traffic density than city roads. All the other cofactors for the development of the speed limit were directly able to be analyzed with the ANCOVA test, and they were found not to contribute. This finding indicates that the planned traffic densities for rural roads were underestimated or the traffic density for rural roads was much lower when the speed limits were set than present day. ADAS software could be written to account for this and alter ADAS criteria and actions if GPS data was incorporated into the ADAS decision scheme.

4.3.3 Result Synopsis for the Industry Leader

The growing availability of ADAS technology, its increased use in FSLDPTs, and the overall truck design have improved the survivability of truck occupants during an accident. The decrease in the overall number of accidents (shown in Tables 12 and 13) and the shift from higher severity injuries to lower severity injuries (detailed in Figures 20 and 21) demonstrates the effectiveness of ADAS at reducing fatalities. Most hazardous events are vehicles in motion colliding with each other. ANCOVA testing determined that the speed limit coupled with the road being rural or urban affected the injury level of ADAS equipped vehicles. Thus, ADAS could be further improved by incorporating GPS data for determining when to alert or take action. The road being rural or urban appears to be a significant factor in ADAS performance.

4.4 Investigating Economics of the Seven FSLDPT High-End Models

The FARS data from NHTSA was analyzed in several stages. The data was initially evaluated to determine how certain factors for a particular year correlated with severity of injury to the FSLDPT occupants and level of damage that the FSLDPT sustained. This was then extended to show how these factors' contribution with respect to severity of injuries and level of damage changed over multiple years. After stratifying the FSLDPTs as 1) high-end with ADAS, 2) high-end without ADAS, 3) low-end, the severity of injury was evaluated for each stratum. Vehicle sales data, obtained from company 10-K reports, a mandatory comprehensive report of publicly traded companies for the Security and Exchange Commission (SEC)(Fields and Shanks 2015, 2016, Groff and Ballinger 2015, 2016, Barra and III 2015, 2016, 2017, Kaczynski 2015, 2016, 2017, Marchionne and

Palmer 2015, 2016, 2017, Moroe and Kubaru 2015, 2016, 2017, Groff and Chu 2017, 2018, Hackett and Shanks 2017, 2018, Barra and Suryadevara 2018, Cullum 2018, Manley and Palmer 2018, Moroe and Nakamura 2018), and online web searches (2020), were used for normalization. The normalization was performed by copying the data previously evaluated and dividing it by the number of FSLDPTs of the corresponding model were sold each year.

ANOVA tests were conducted to determine the statistical significance of findings. The ANOVA test (analysis of variance test) is a stochastic tool that compares the variances of two or more groups of data. The ANOVA test determines if the datasets are in fact the same datasets or different distinct sets of data. If there is no real difference between the datasets, the null hypothesis, the result of the ANOVA P-value (or F-ratio) will be near 1, and if there is a significant difference between the datasets, the result of the ANOVA P-value will be less than 0.05. In this research a one-way ANOVA is used with the independent variable used in the test is the Level of Injury. The one-way ANOVA is selected over the two-way ANOVA due to the other possible variable for comparison (Damage Severity) not being independent of Level of Injury. The total numbers of accidents, fatalities, and no injuries from 2016 through 2018 were tallied for two bands of vehicle model years (<2015 and ≥2015). These two bands represent the vehicle model years prior to ADAS and post ADAS. For most auto manufacturers the ADAS introduction vehicle model year is 2015 for FSLDPTs, but Honda introduced ADAS in there 2017 model year for FSLDPTs due to a temporary discontinuous of their FSLDPT. A single factor ANOVA test was performed for the high-end vehicle models comparing the bands for the high-end vehicle models. High-end vehicle models with and without ADAS were selected for the comparison rather than high-end versus low-end as a means to keep as many factors constant such as cabin style or engine size. It is also important to note that accidents were not compared between accident years so as to avoid the potential for laws changing between accident occurrences. If there is a statistical difference (P-value < 0.05), then the comparison of ADAS to non-ADAS vehicles would indicate there was either an improvement or depreciation in the survivability of the FSLDPT.

4.4.1 ADAS Technology Costs

The SBD USA ADAS & Autonomy database (Automotive 2019), details the ADAS technologies in over 500 models including who produces the technologies for the vehicles, list the cost of ADAS technologies. It also states who the suppliers are for each technology, for example both GMC and Chevrolet use ZF for their respective lane departure prevention systems. There are some shortcomings from the database as not all technologies are listed; however, this is consistent across all brands. The consistency means that even if a technology, is missing it is missing across the board allowing the comparison to still be valid. The database did not provide any data regarding the Honda Ridgeline. Even so, the Honda Ridgeline represents a very small segment of the vehicle population. By comparing cost for the ADAS technologies across brands for FSLDPTs a determination can be made about which suppliers produce an effective safety product and at what price point. The result of which can be used to determine if there is a threshold cost for the ADAS technology packages before desirable outcomes, reduction in fatalities and fatal accidents, occur.

4.5 Economic Outcomes Based on ADAS Effectiveness for FSLDPTs

Through evaluation of several makes and models involved in accidents from 2015 to 2018, a portrait of the cost effectiveness of ADAS technology at reducing the severity of injuries from accidents has been developed. The Ford F-150, Chevrolet Silverado, GMC Sierra, RAM 1500, Toyota Tundra, Nissan Titan, and Honda Ridgeline were the FSLDPTs identified for the comparison in this study.

4.5.1 ADAS Effectiveness for Different FSLDPT High-End Models With and Without ADAS

As mentioned before, high-end and low-end models were stratified in the FARS datasets by using the information obtained from the auto manufacturer's sales brochures. The high-end models were further delineated into those that possessed ADAS and those that did not possess ADAS. This allowed for greater insight into how ADAS affects FSLDPT safety. Low-end models in most cases did not possess ADAS technology except when a technology was mandated by law. Table 15 delineates the information about the high-end FSLDPTs between those with ADAS and those without ADAS for the different injuries sustained during accidents. The RAM 1500 consistently has much lower injury counts across all injury severities for high-end FSLDPTs without ADAS than FSLDPTs with ADAS. During RAM's transition to incorporating ADAS in their FSLDPTs the company changed ownership from Dodge to Chrysler Fiat. The change in ownership appears to account for the large disparity in quantity of injuries. There may be outstanding differences in vehicle quality between RAM owned by Dodge and RAM owned by Chrysler Fiat that is beyond the scope of this study. The other vehicle model FSLDPTs did not change ownership; however, the Honda Ridgeline was discontinued in 2015 and brought back with ADAS in 2017.

Table 15. Table of high-end ADAS and non ADAS injuries in the 2018 FARS data for each of the seven FSLDPTs.

Make & Model	Injury Level	ADAS 2016	High w/o 2016	Difference (%) 2016	ADAS 2017	High w/o 2017	Difference (%) 2017	ADAS 2018	High w/o 2018	Difference (%) 2018
CHEVY Silverado	0	27	78	65%	71	51	-39%	55	68	19%
	1	20	36	44%	16	25	36%	24	23	-4%
	2	14	34	59%	21	31	32%	27	25	-8%
	3	10	23	57%	5	19	74%	15	27	44%
	4	16	54	70%	15	58	74%	28	50	44%
GMC Sierra	0	15	15	0%	9	5	-80%	15	11	-36%
	1	0	5	100%	3	2	-50%	6	4	-50%
	2	2	3	33%	4	7	43%	12	3	-300%
	3	3	6	50%	2	1	-100%	1	0	-
	4	2	9	78%	2	8	75%	5	1	-400%
RAM 1500	0	100	3	-3233%	103	5	-1960%	186	9	-1967%
	1	41	4	-925%	46	3	-1433%	51	3	-1600%
	2	54	4	-1250%	58	3	-1833%	65	3	-2067%
	3	38	4	-850%	29	3	-867%	37	3	-1133%
	4	53	4	-1225%	72	3	-2300%	84	3	-2700%
TOYOTA Tundra	0	0	21	100%	2	13	85%	1	14	93%
	1	1	1	0%	1	8	88%	0	5	100%
	2	0	3	100%	2	4	50%	0	2	100%
	3	0	2	100%	2	2	0%	2	1	-100%
	4	0	3	100%	1	7	86%	2	2	0%
HONDA Ridgeline	0	0	1	100%	2	11	82%	0	2	100%
	1	0	0	-	0	3	100%	0	3	100%
	2	0	0	-	0	2	100%	1	1	0%
	3	0	0	-	0	0	-	1	1	0%
	4	0	0	-	0	5	100%	0	6	100%
NISSAN Titan	0	0	4	100%	12	14	14%	10	19	47%
	1	1	0	-	4	2	-100%	5	3	-67%
	2	1	3	67%	3	3	0%	9	5	-80%
	3	0	0	-	6	4	-50%	10	4	-150%
	4	1	4	75%	8	11	27%	13	10	-30%
FORD F-150	0	1	47	98%	11	153	93%	40	102	61%
	1	0	12	100%	6	60	90%	12	24	50%
	2	3	13	77%	8	88	91%	17	35	51%
	3	0	14	100%	5	33	85%	3	27	89%
	4	2	38	95%	16	143	89%	13	184	93%

When looking at the totals for each FSLDPT, there are considerable differences in sales between the seven FSLDPTs. Ford sold nearly a million FSLDPTs in 2018 with Chevrolet and RAM having each sold about half as many and GMC sold approximately a quarter of the total FSLDPTs as Ford, respectively. The remaining three FSLDPT models combined sold bellow the number of GMC FSLDPTs.

4.5.1.1 ANOVA Testing of ADAS Effectiveness

The ANOVA test results for all the FSLDPT models are listed in Table 7. ANOVA tests were conducted for each of the seven FSLDPT models for three different injury severity groupings (No Injury, All Injuries, Fatal Injuries) from 2016 to 2018. For reducing fatal injuries in their respective vehicle, the Ford F150 and Chevrolet Silverado were statistically significant. The RAM 1500 was also statistically significant, but as show in Table 15, statistically significance was detrimental rather than advantageous with more fatalities occurring in the ADAS equipped vehicles. This trend of the RAM 1500 being statistically significant in a detrimental manner continued for the other three ANOVA tests.

The number of the High-end models both with and without ADAS involved in fatal accidents are small, but that is a factor of there being approximately 40,000 vehicles total involved in fatal accidents for the approximately 240 million registered vehicles in the United States. This study is only looking at the high-end models of FSLDPTs which make up a small portion of the FSLDPTs sold each year further reducing the likelihood for large vehicle numbers.

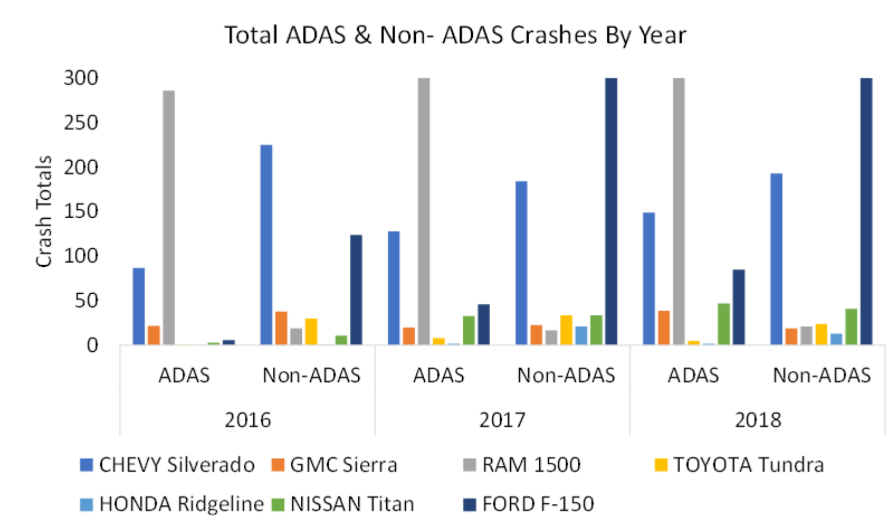

Figure 22. Totals for crashes of high-end FSLDPTs with ADAS versus those without ADAS broken out by year.

For reducing all injuries, the Ford F-150, the Chevrolet Silverado, and the Toyota Tundra were statistically significant. The all injuries analysis includes the fatal injury and the no injury totals. From reviewing the totals, the fatality reduction for Chevrolet and the no injury reduction for Toyota is what drove the statistical significance for the all injuries analysis for those two FSLDPT models. The Ford F-150 had fewer injuries for all individual injury severities. This all injuries category can be viewed as representing as an all fatal crashes category.

For the occurrence of no injuries ANOVA test, the Ford F-150 and the Toyota Tundra were statistically significant. For the no injury severity totals, both the F-150 and the Tundra had fewer instances with ADAS equipped vehicles than with unequipped vehicles. While intuitively this seems in opposition to the desired outcome, it in fact is advantageous. Holistically these results show there were fewer accidents with the ADAS equipped FSLDPTs contributing to the lower totals for no injuries as shown in Figure 22.

4.5.2 *Influence of ADAS Technology Costs*

The differences between the varying manufacturers' FSLDPT models' performance potentially lies with their choices for ADAS technologies. According to the SBD, each manufacture uses a unique combination of third-party suppliers for their ADAS technologies. RAM 1500 and Nisan Titan ADAS costs the least at $1695 and $1640 respectively (Automotive 2019). The three FSLDPT models that were statistically significant Chevrolet, Ford, and Toyota ADAS costs were $3510, $3875, $2180 respectively (Automotive 2019). No data was listed for the Honda Ridgeline. A full cost breakdown is provided in Table 16. Two FSLDPT models of interest are the Chevy Silverado and the GMC Sierra. These two companies use the same third-party sensor suppliers and the cost for the sensors are similar except for Blind Spot Monitoring (BSM), Rear Cross Traffic Alert (RCTA), and Surround View Cameras (SVC). For the three sensors that are different GMC has a higher cost for them; however, Chevy not GMC showed statistical improvement for reducing fatal injuries. Two of these sensors, RCTA and SVC, should not contribute much to reducing fatal injuries as they are generally used in low-speed parking situations. BSM would be useful in preventing the most common harmful event, moving vehicle collision, but the GMC sensor costs more than the Chevy sensor. Also, the most common initial point of impact on FSLDPTs is across the front bumper region where BSM would not play a definitive role in accident prevention or injury severity reduction. This means that there is a minimum amount that ADAS should cost to have the potential to be effective, namely, about $2000 - $3000, but above that amount does not guarantee effectiveness.

Table 16. Cost breakdown for ADAS sensors of FSLDPTs. Numbers denote cost in dollars and numbers preceded by the letter B are part of a bundle.

	ACC	**COLLISION AVOIDANCE**	**LK**	**BSM**	**RCTA**	**DRIVER MONITORING**	**AHB**	**PA**	**TRAILER ASSIST**	**SVC**	**TOTAL**
CHEVY SILVERADO 1500	-	B745	B745	B890	B890	-	B745	-	-	1875	3510
FORD F-150	500	-	B1195	B1585	B1585	B1195	-	B1195	595	B1195	3875
GMC SIERRA 1500	-	B745	B745	B1315	B1315	-	B745	-	-	1845	3905
HONDA RIDGELINE	-	-	-	-	-	-	-	-	-	-	-
NISSAN TITAN	-	-	-	B845	B845	-	-	-	-	795	1640
RAM 1500	B1695	B1695	B1695	B1695	B1695	-	B1695	B1695	-	B1695	1695
TOYOTA TUNDRA	-	-	-	B2180	B2180	-	-	-	-	-	2180

Besides the upfront cost of having a FSLDPT with ADAS, per [121] approximately 5% – 15% of the initial cost, the cost for seemingly minor repairs has increased as depicted in Table 17. In some cases the cost for repair of ADAS capable parts has doubled while in more extreme cases increased by over twelve times the cost for a non-ADAS version of the part (Association 2018, Preston 2020). This does not seem right or in the consumer's best interest for the cases where the addition of ADAS to the FSLDPTs did not statistically change accident rates from those without ADAS. Consumers are charged thousands of dollars upon vehicle purchase for a feature that is supposed to prevent and minimize accidents but that per above study result does potentially not do this as advertised. Furthermore, consumers are charged again for thousands of dollars when it needs to be replaced when it was in accident that it did not prevent. For the cases where there was a statistical improvement (Ford F-150, Chevy Silverado, and Toyota Tundra) from the inclusion of ADAS, an argument can be made for the increase in repair costs as being necessary to keep the FSLDPT effective at reducing accidents and injury severity.

Table 17. Cost of vehicle part repairs/replacements based on (Association 2018, Preston 2020).

PART	REPLACEMENT	MIN	MAX
FRONT BUMPER	Basic Bumper	700	1800
	Sensors	500	1900
	Recalibration	250	600
	Total	1450	4300
HEADLIGHTS AND TAILLIGHTS	Halogen	200	500
	LED	750	1500
	Recalibration	100	250
	Total	300	1750
WINDSHIELD	Regular	300	500
	ADAS-capable	700	1500
	Sensors	800	1900
	Recalibration	250	250
	Total	1750	3650
REAR BUMPER	Basic Bumper	700	1800
	Sensors	1000	2500
	Recalibration	250	250
	Total	1950	4550
SIDE MIRROR	Regular	300	500
	ADAS-capable	1000	2500
	Recalibration	250	250
	Total	1250	2750

4.5.3 Economic Effectiveness Synopsis

With the ever more availability of ADAS technology in FSLDPTs, the increased use of ADAS and overall truck design has shown the potential to improve the survivability for truck occupants during an accident. There is the potential need for several FSLDPT manufacturers to reassess their ADAS technologies to be on par with the improvements found in Ford's F-150 and Chevrolet's Silverado as detailed in Table 8 and discussed in section 4.2.1 (ANOVA Testing of ADAS Effectiveness). Of the 18% of registered vehicles, slightly more than half show improvement in reduction of injuries and fatalities. For the half that showed improvement, the cost for the technologies were over $2000. Those whose ADAS costs below $2000 should seek to change their sensors. Those who's ADAS cost meet or exceeded the $2000 - $3000 threshold, but were still not effective, should see about altering the positioning of them on the FSLDPTs to achieve a statistical improvement in accident reduction and injury severity reduction as found in (Fish and Bras 2021).

In (Fish and Bras 2021) the positioning of crash impact location was optimized to identify the best and worst positions for a FSLDPT to be impacted based on ADAS effectiveness. Using (Fish and Bras 2021) automotive manufacturers can further improve the effectiveness of their deployed ADAS technologies. The half of the FSLDPTs - GMC, Honda, Nissan, and RAM - that did not show improvement in safety should be regarded as providing features of convenience. There are cases where the increase in costs does make sense even though safety effectiveness is not improved during fatal accidents. For example, the backup camera may reduce the need for repairs from minor crashes by providing the driver an advantageous view of the rear area, which would save on bumper repairs. Spending more than \$2000-\$3000 on ADAS is not an absolute for determining effectiveness, but it is a decent first indicator.

It is interesting that Chevrolet showed improvement while GMC did not. Both companies are subsidiaries of General Motors and have similar vendors for ADAS sensors. This is talked more about in (Fish and Bras 2021). How the ADAS technologies are deployed on the vehicle becomes more important for determining the effectiveness of ADAS for vehicles with ADAS costing over \$2000- \$3000. The near identical technologies deployed on both the Chevrolet Silverado and the GMC Sierra show that the quality of sensors is the same. While not confirmed, the likelihood that the Silverado and the Sierra have the same positioning of ADAS sensors is minimal. This likely means based on the findings of (Fish and Bras 2021) that the position of the sensors becomes more important after the proper investment has been made in the sensor technologies. The inclusion of

ADAS has not only increased the initial investment in FSLDPTs but also increased the repair costs by a significant multiple. For the cases where ADAS reduced accidents and injury severities, this increase may be reasonable. However, for those cases where ADAS did not make a statistical difference the increased cost to the consumer may not be warranted. There are cases where the increase in costs does make sense even though safety effectiveness is not improved during fatal accidents. For example, the backup camera may reduce the need for repairs from minor crashes by providing the driver an advantageous view of the rear area, which would save on bumper repairs.

4.6 Minor Findings

Outside of the major findings from the datamining portion of this research, there were minor findings that extend existing findings from general vehicle studies to specifically the FSLDPT. One such finding is the ratio of FSLDPT accidents for rural roads to urban roads. Motor vehicle deaths prior to 2016 primarily occur on rural roads and are usually only separated by a few percent (Institute 2019, NHTSA 2019). For FSLDPTs that breakdown is consistent for FSLDPT crashes. Interestingly, when looking at fatalities in the FSLDPT the split becomes 60-40, rural-urban, and FSLDPTs with ADAS follow this split. There is an exception for FSLDPTs with ADAS, where there is reverse 40-60 split for fatalities rural-urban occurring in 2017. An example of this mapping is shown in Figure 23 and more figures of the mapping by brand are shown in Appendix A.

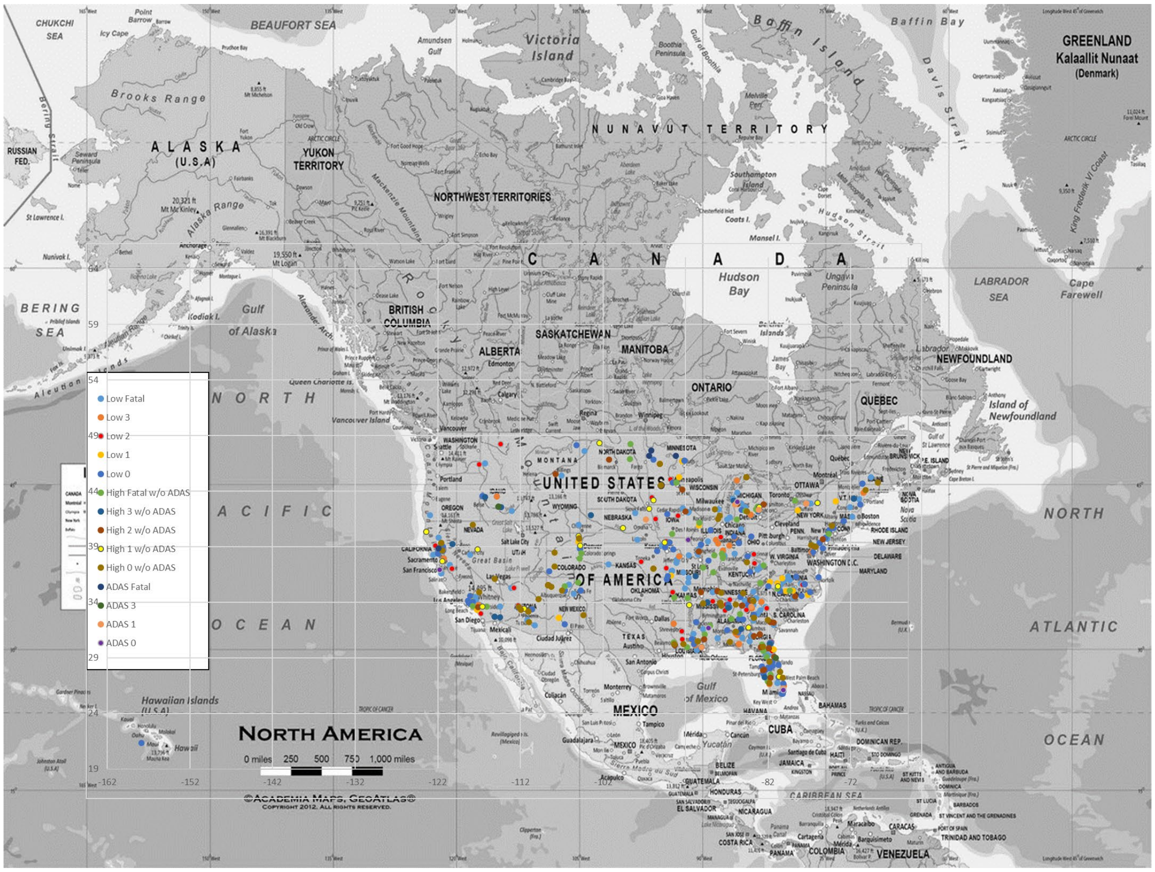

Figure 23: Map of 2016 Ford accidents based on injury severity in the FSLDPT.

4.7 Summary and Conclusions

As dissemination of ADAS technology continues from high-end models to lower-end models, FSLDPT occupants will likely see greater decline in fatalities and sever injuries for some brands, while other brands may continue to not see a change in their injury reductions as was shown in Table 7. This pattern will continue until those auto manufacturers that have not proven advantageous reassess how they equip their respective FSLDPTs with ADAS technologies. Those that did show statistically significant improvement in safety, through the addition of ADAS technologies, are reassuring since FSLDPTs represent 18% of registered vehicles in the US. It is also a positive that the Ford

F-150 the most sold FSLDPT in the US and the Chevrolet Silverado the second most sold FSLDPT in the US both were found to be statistically improved at reducing fatalities, with the F-150 showing improvements at reducing all injury severities even when adverse driving conditions were present. This is best enlightened by the finding that the Ford F-150, when equipped with ADAS, provided ample time to the driver to alter the situation that impaired drivers were better able to avoid accidents. The Toyota Tundra demonstrates how ADAS was able to outperform non-ADAS during inclement weather, which shows that the interlacing of sensors is capable to reducing human error during inclement weather. The characteristics of FSLDPTs (heavier, less maneuverable, with large blind spots) generally increase the severity of accidents, but the adoption of ADAS has been proven to reduce fatalities and sever injuries in some models. These trends will likely continue as ADAS technology expands into new areas while diminishing the possibility for human error. Application of this research are already being seen in the insurance premium reductions for ADAS vehicle drivers. Further applications of this research in conjunctions with (Fish and Bras 2021) include changes to sensors, sensor positioning, and vendors who are contracted for the production of ADAS sensors.

CHAPTER 5. THE RESULTANT OF THE CONTINUED TRAJECTORY OF PRESENT ADAS DEVELOPMENT

The object of this chapter is to identify the specific areas of ADAS coverage whose improvements through design would financially make the greatest impact. This chapter expands on the work of (Fish and Bras 2021), which focused on the Ford F-150 representing 9% of registered vehicles in the United States. This chapter looks at six of the seven main FSLDPT, which account for 18% of registered vehicles in the United States, to be studied as it offers an opportunity to impact a large segment of the vehicle population.

5.1 METHODOLOGY – An Optimization Approach

The purpose of the methods used herein is to determine how to improve ADAS based on empirical data. Using a compilation of data from several sources, models of the costs and injury severities associated with ADAS in the Ford F-150, Chevrolet Silverado 1500, GMC Sierra 1500, RAM 1500, Toyota Tundra, and Nissan Titan were developed. The models were then run through optimization tools in MATLAB to determine the best and worst locations of impact on the FSLDPTs. While the FSLDPTs were selected for this work, any vehicle could be substituted for these processes.

5.2 OBJECTIVE FUNCTION DEVELOPMENT

The real-world accident data regarding FSLDPTs with ADAS was taken from the National Highway Traffic Safety Administration (NHTSA). The NHTSA Fatality Analysis Reporting System (FARS) database was selected because it provided the most complete and detailed publicly available data concerning automotive accidents in the United States.

The FARS data stratifies injuries into 5 main severity levels ranging from 0 (no injury) to 4 (fatality). The first impact locations, reported in FARS, are discretized broken into twelve main segments, 1-12, as shown in Figure 24 with a thirteenth option being no impact, 0 (NHTSA 2018). It is important to note that all accidents reported in FARS involve at least one fatality. The injury severity range indicates individual occupant injury in each vehicle. It is possible for occupants of one of the vehicles in a multivehicle accident to have no fatalities.

Table 18. Average financial cost by injury severity taken from 2018 (National Safety Council 2020).

Injury Level	Cost	Injury Level (#)
Death (K)	$1,659,000	4
Disabling (A)	$96,200	3
Evident (B)	$27,800	2
Possible (C)	$22,800	1
No injury observed (O)	$12,200	0

Automotive accidents were broken into two categories concerning the costs associated with the accident:

- Costs associated with vehicle occupant injuries and
- Costs for the repair/replacement of the vehicle component(s) damaged.

First, the cost associated with the occupant injuries, obtained from (National Safety Council 2020), were discretized to match with the FARS injury levels as shown in Table 18. With the five data points, from Table 18, discretized into the 5 injury levels a non-linear regression was performed to obtain Equation 3.

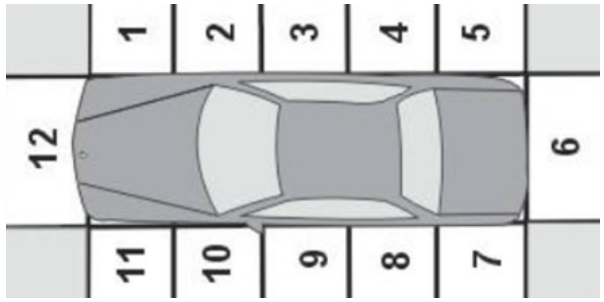

Figure 24. Areas of Impact for initial contact point diagram (NHTSA 2018).

In Equation 3, the five discretized injury levels are associated with the injury cost (IC) represented by the independent discrete variable x_1, injury severity.

$$InjuryCost = 56750x_1^4 - 329000x_1^3 + 586950x_1^2 - 304100x_1 + 12200 \quad (3)$$

The data for the repair/replacement of vehicle components cost associated with automotive accidents is comes from (Association 2018, Preston 2020). These repair costs (RC) can be divided into ADAS (maximum repair cost) and non-ADAS (minimum repair cost). These costs are distributed amongst their corresponding positions as shown in Table 19.

Table 19. Cost of repairing vehicle components (Association 2018, Preston 2020).

Component	Max Cost	Min Cost	Position
Front Bumper & Lights	$5,175	$1,600	12
Rear Bumper & Lights	$5,425	$2,100	6
Right Mirror	$1,375	$625	3
Left Mirror	$1,375	$625	9
No Damage	$0	$0	0

Plotting these two repair cost levels against their position, as done in Figures 25 and 26, shows how the repair cost (as in Equations 4 and 5), is orders of magnitude smaller than injury costs (per Equation 3). To get better results from the simulations, the value for impact zone 0 (no impact) was set to be the same as zone 12 (front bumper) as indicated in Figure 26. The reason for this is that the results from using Equation 4 in (Fish and Bras 2021) were found to cause asymmetry on the results of the simulation. Thus, Figure 26 and Equation 5 are used in this work.

$$RepairCost = 15.972x_2^3 - 313.29x_2^2 + 1890.8x_2 - 381.79 \tag{4}$$

$$RepairCostAdjusted = 16.409x_2^4 - 393.83x_2^3 + 2946.8x_2^2 - 7005.6x_2 + 5175 \tag{5}$$

The purpose of this work is to determine which ADAS zones of the FSLDPT can be improved, so the regression equation for maximum repair cost was selected as it represents vehicles with ADAS, as shown in Figure 26. In Equations 4 and 5, the independent variable x_2 is the discrete vehicle location for impact.

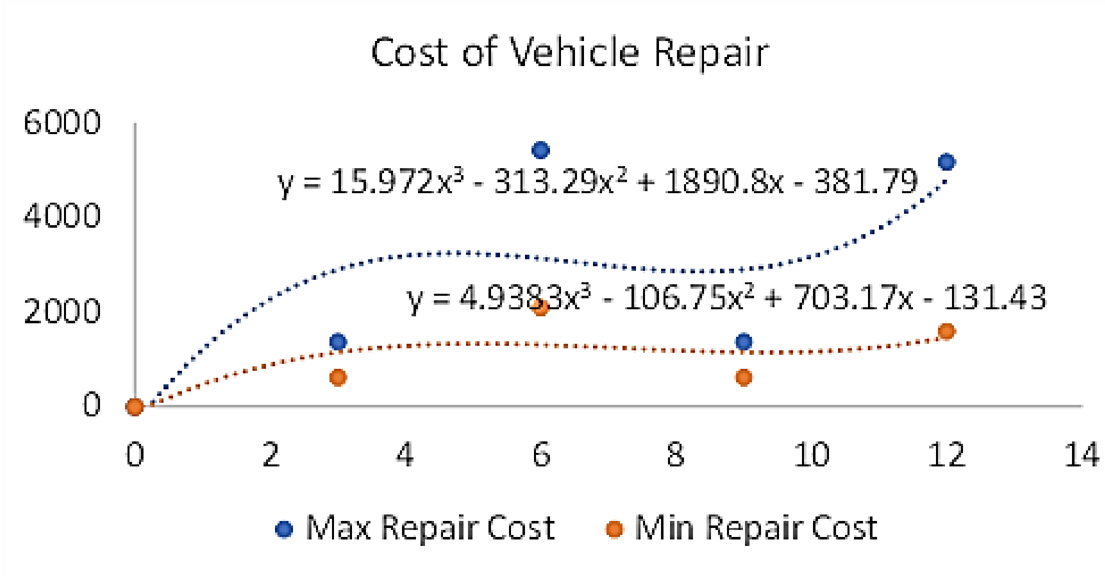

Figure 25. The min and max vehicle repair cost curves.

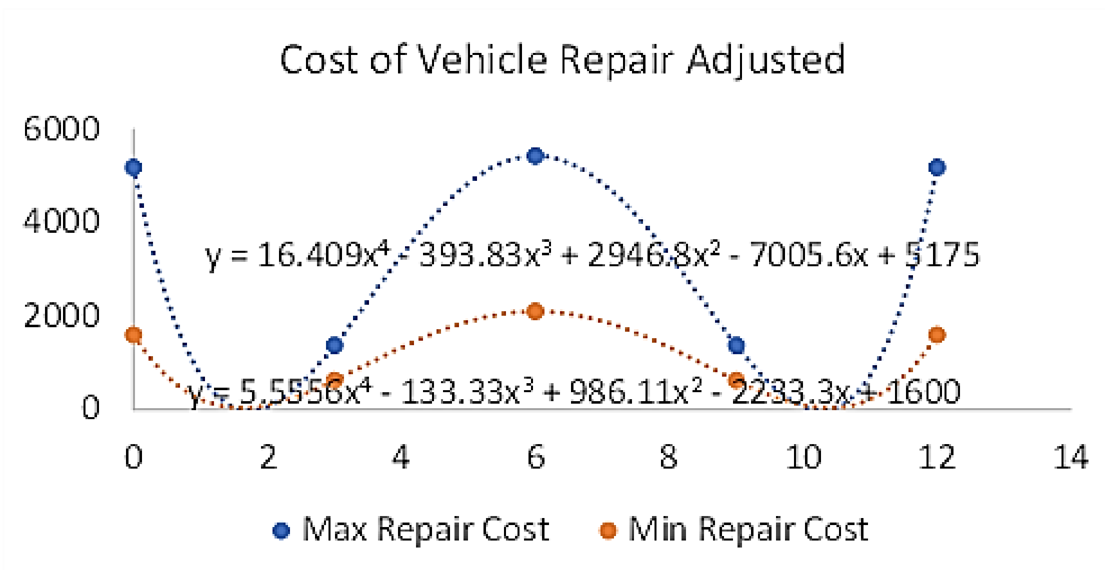

Figure 26. The min and max vehicle repair cost curves adjusted.

Equations 3 and 5 are combined to form the objective function denoting Accident Cost (AC) per Equation 6, which shows that less expensive accidents would be driven by the vehicle repair costs, and the more expensive accidents are driven by the occupant injury costs. This is realized by the injury severity (x_1) quadratic term having a multiple over 100 times the size of both impact location (x_2) cubic and quadratic terms. Both x_1 and x_2 are discrete small values decreasing the effect of the powers of the x_1 and x_2 terms.

$$Obj.Funct.\ AccidentCost = 16.409x_2^4 - 393.83x_2^3 + 2946.8x_2^2 - 7005.6x_2 + 12971x_1^2 - 13806x_1 + 19938 \quad (6)$$

5.3 CONSTRAINT FUNCTIONS DEVELOPMENT

The development of the constraint function for initial upfront cost for ADAS technologies looked at two sources for the initial costs. First, the Boston Consulting Group had published a few papers on what people were willing to pay versus the actual cost of ADAS technologies (Mosquet, Andersen et al. 2015, Mosquet, Andersen et al. 2016). Their report used averages of costs for technologies, produced in Table 20.

Table 20. Boston Consulting Group cost of ADAS components (Mosquet, Andersen et al. 2015, Mosquet, Andersen et al. 2016).

ADAS	Cost ($)
360 view	900
Park assist	250
Lane departure	400
Blind spot	600
ACC/FCW/FCA	1,500
Auto Park	400

From Table 20 an initial ADAS technology cost curve equation (Equation 7) was extracted based on positioning of the technology on the vehicle.

$$ConstraintCost: 2.0436x_2^4 - 47.119x_2^3 + 353.57x_2^2 - 948.08x_2 + 898.46 \geq 2000 \quad (7)$$

Equation 7 for the constraint cost (CC) uses averages from all vehicles' ADAS technology initial costs. As detailed in (Fish and Bras 2021, Fish and Bras 2021), $2000 was the minimum cost of ADAS that were found to be effective at preventing crashes and reducing injury severity during crashes. A database for the cost of ADAS technologies for specific vehicles was found. (Automotive 2019) had ADAS costs for the FSLDPT specifically, so a better relation was developed by using those values for the related positions on the vehicle as shown in Figure 27. Interestingly the rear bumper was found to be the most expensive zone on the FSLDPT due to the addition of trailer backup technology.

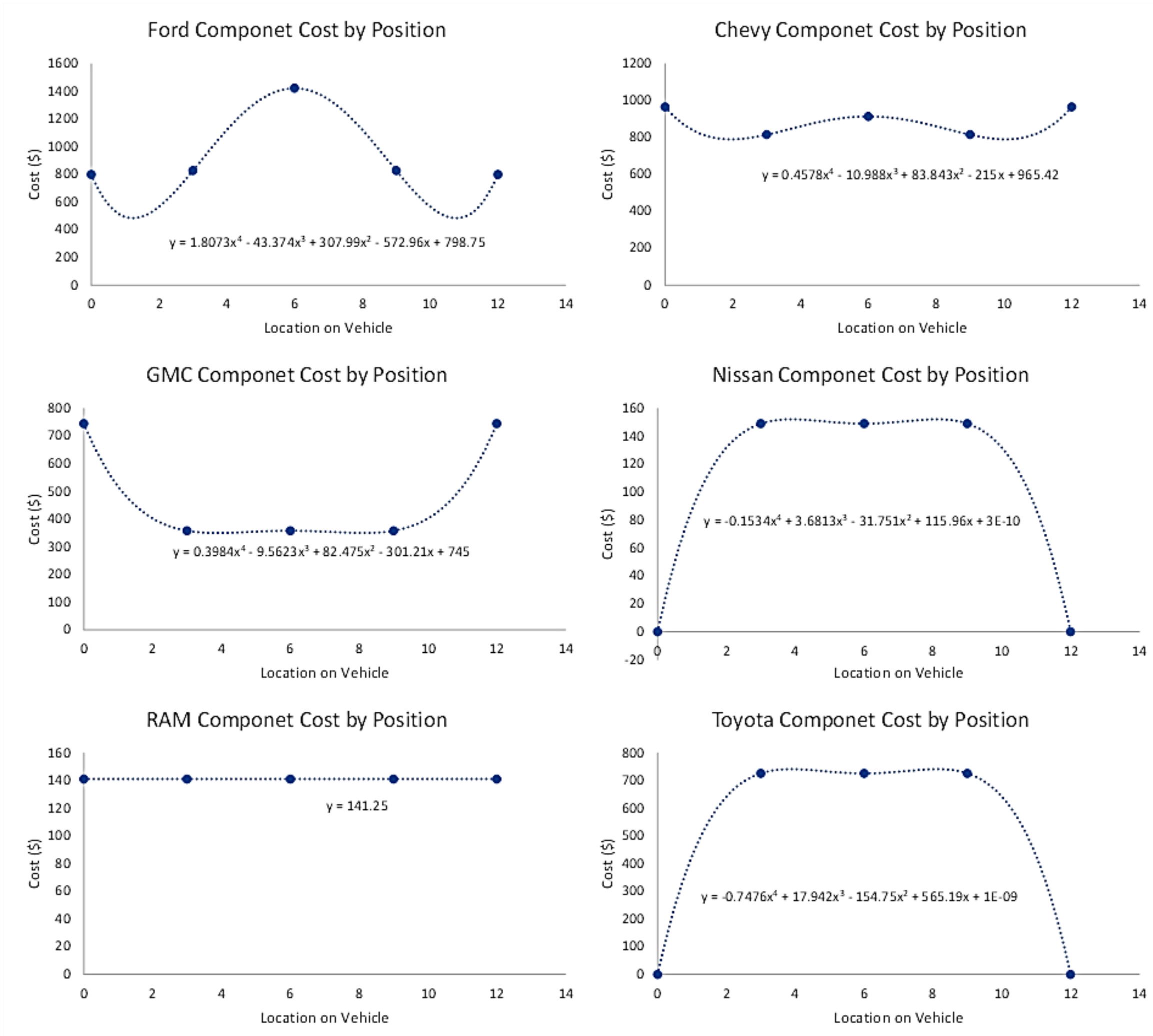

Figure 27. The component ADAS cost for position on the vehicle.

It was decided to use Equations 8 – 13 for the constraint cost (CC) for the component cost instead of Equation 7 because Equations 8 – 13 is specific for the Ford F-150, Chevrolet Silverado, GMC Sierra, Nissan Titan, Ram 1500, and Toyota Tundra. The inequality for Equations 7 – 13 of greater than or equal to 2000 is the median for the ADAS initial costs of the FSLDPTs listed in (Automotive 2019). Worth noting is that RAM had a constant for its' ADAS cost as shown in Equation 12. Hence RAM is not being optimized, but it is still included in the analysis.

$$ConstraintCostFord: 1.8073x_2^4 - 43.374x_2^3 + 307.99x_2^2 - 572.96x_2 + 798.75 \geq 2000 \quad (8)$$

$$ConstraintCostChevy: 0.4578x_2^4 - 10.988x_2^3 + 83.843x_2^2 - 215x_2 + 965.42 \geq 2000 \quad (9)$$

$$ConstraintCostGMC: 0.3984x_2^4 - 9.5623x_2^3 + 82.475x_2^2 - 301.21x_2 + 745 \geq 2000 \quad (10)$$

$$ConstraintCostNissan: -0.1534x_2^4 + 3.6813x_2^3 - 31.751x_2^2 + 115.96x_2 + 3 \times 10^{-10} \geq 2000 \quad (11)$$

$$ConstraintCostRAM: 1695 \geq 2000 * \quad (12)$$

$$ConstraintCostToyota: -0.7476x_2^4 + 17.942x_2^3 - 154.75x_2^2 + 565.19x_2 + 1 \times 10^{-9} \geq 2000 \quad (13)$$

5.4 MATHEMATICAL OPTIMIZATION

Some assumptions were made to create the optimization model and interpret the results. The model was built using discrete data; however, the equations are continuous as explained in sections 2.1 and 2.2 and shown in Figure 28. This was allowed to account for the cost of damage in zones where the ADAS components are not physically located. It is also used round to the nearest impact zone, but the decimal is used to gain perspective on the location in the zone. Other assumptions made involved not adjusting the offsets for cost of injury when there was no injury.

$Obj\ Fun.AccidentCost = 16.409x_2^4 - 393.83x_2^3 + 2946.8x_2^2 - 7005.6x_2 + 56750x_1^4 - 329000x_1^3 + 586950x_1^2 - 304100x_1 + 17375$

Subject to:

$ConstraintCostFord: 1.8073x_2^4 - 43.374x_2^3 + 307.99x_2^2 - 572.96x_2 + 798.75 \geq 2000$

$ConstraintCostChevy: 0.4578x_2^4 - 10.988x_2^3 + 83.843x_2^2 - 215x_2 + 965.42 \geq 2000$

$ConstraintCostGMC: 0.3984x_2^4 - 9.5623x_2^3 + 82.475x_2^2 - 301.21x_2 + 745 \geq 2000$

$ConstraintCostNissan: -0.1534x_2^4 + 3.6813x_2^3 - 31.751x_2^2 + 115.96x_2 + 3 \times 10^{-10} \geq 2000$

$ConstraintCostRAM: \sum_1^{12} 141.25\ X2?? \geq 2000$

$ConstraintCostToyota: -0.7476x_2^4 + 17.942x_2^3 - 154.75x_2^2 + 565.19x_2 + 1 \times 10^{-9} \geq 2000$

x1: Injury Severity [0 - 4]

x2: Impact Location [0 - 12]

Objective: Determine the minimum and maximum cost for an ADAS equipped FSLDPT.

Figure 28. Optimization problem for determining the optimum ADAS locations on a FSLDPT.

The software used for the optimization was MATLAB R2019a (The MathWorks 2020). The objective function, Equation 6, and the constraint function, Equations 8 – 13, were entered into two optimization solvers in the MATLAB optimization toolbox – fmincon and fminunc– pictured in Figure 29. Fmincon is for constrained non-linear optimization, whereas Fminunc is for unconstrained non-linear optimization. Both will require the change the objective function to find the maximum and minimum as the relation between maximum and minimum is described in Equation 14. In order to find the maximum unconstrained solutions, fmincon was used with the objective function altered using Equation 14 with lower and upper bounds set to represent the bounds set by x_1 and

x_2, injury severity and impact location respectively. No constraint function was used in the establishment of the upper unconstrained solutions.

All solvers for the MATLAB optimization toolbox work based on the premises of Equation 15.

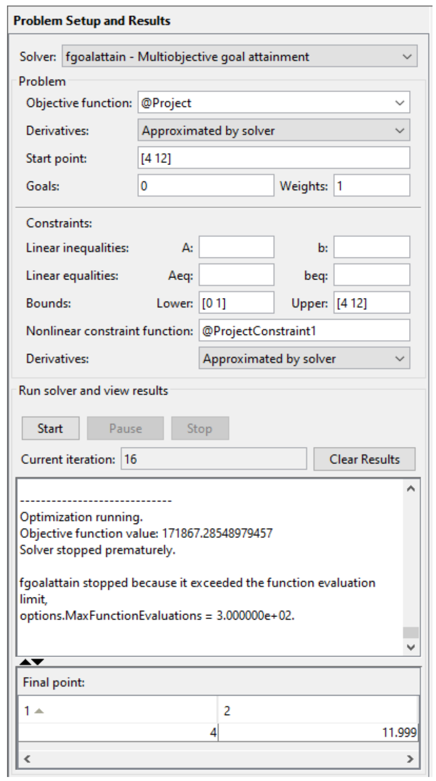

Figure 29. MATLAB optimization toolbox user interface.

$$\min\big(f(\bar{x})\big) = -\max\big(f(\bar{x})\big) \tag{14}$$

$$\bar{X}_{k+1} = \bar{X}_k + \alpha_k \bar{S}_k \tag{15}$$

5.5 RESULTS AND DISCUSSION

The objective is to find the minimum and maximum accident costs for the objective function per Equation 6. The function is bounded to the region of [0, 4] for x_1 and [0, 12] for x_2 as graphed in Figure 30. Figure 30 shows that for more severe injuries the cost of the accident exponentially increases. While the impact zone location effects how quickly the accident cost increases for the severity of injury.

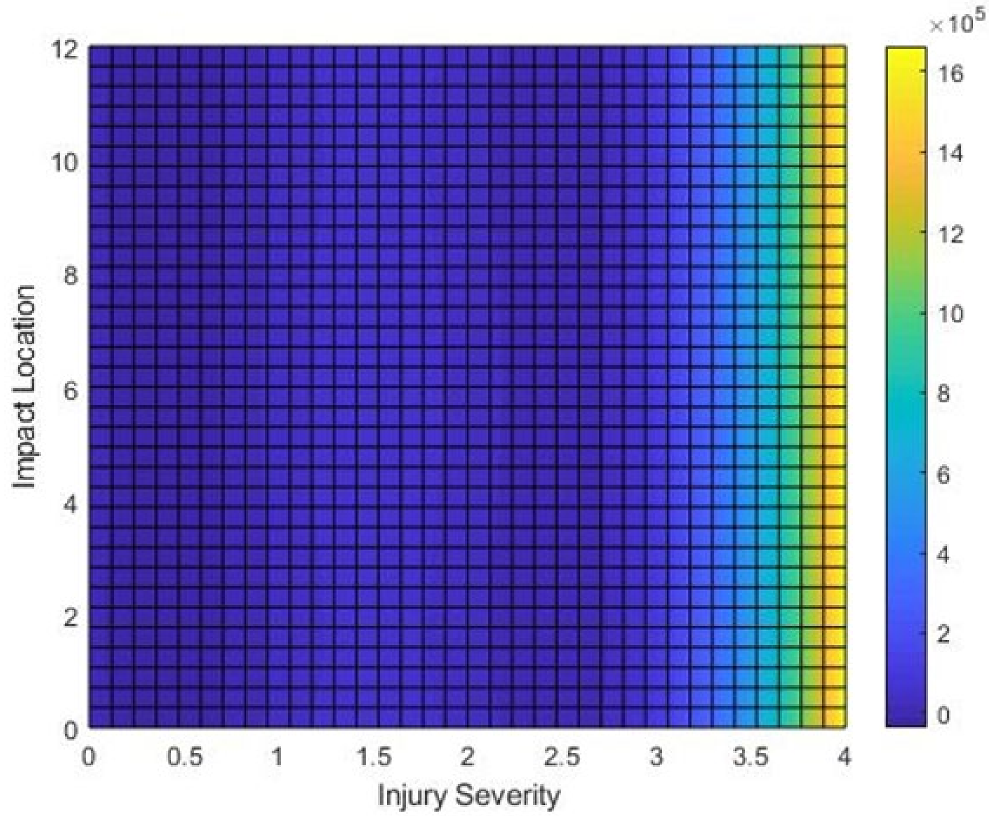

Figure 30. Two-dimensional plot of the objective function for the cost of the accident.

The constraint for this objective is the initial cost for the ADAS components based on the NHTSA impact zones. This is described by the constraint costs (CC) from Equations 8 - 13, which are surface contours were all elevated by 10,000 to allow for intersection with the objective function. Otherwise, the optimizations would be the same as the unconstrained case. Plots of the objective function and the constraint functions are shown in Figure 31. The curved surfaces in Figure 31 are the objective function, and the other surface is the constraint functions for each of the various FSLDPTs.

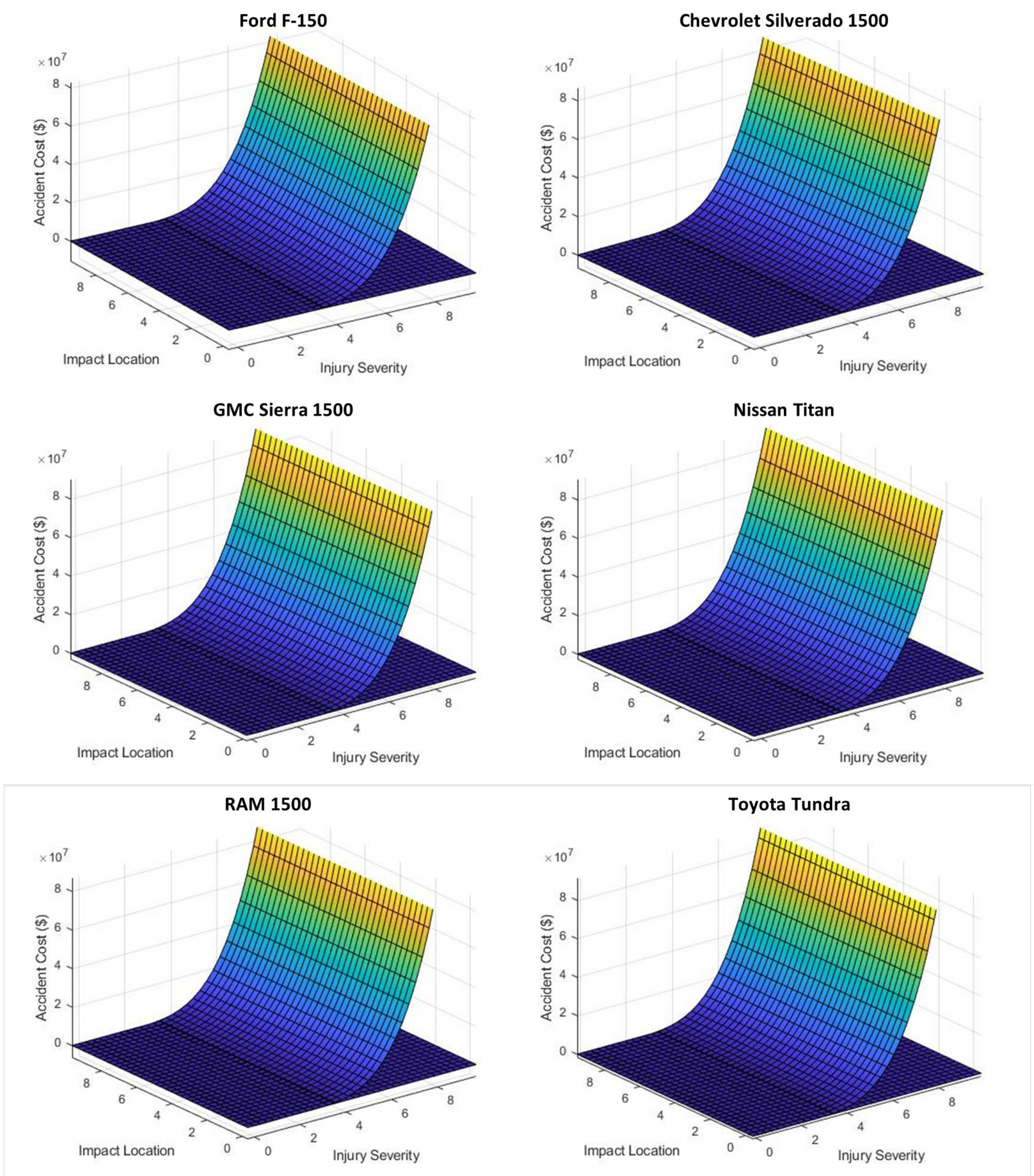

Figure 31. Plots of the objective function intersected by the constraint functions of the six FSLDPTs.

The optimization was run under two separate conditions with the constraint and without the constraint. For both conditions various starting points were selected for evaluation by using the solver methods from the optimization toolbox. The maximum and minimum costs of accidents were evaluated using the maximum minimum relationship of Equation 14. This only mattered for the fmincon solver, as fminunc solver was only used for finding the unconstrained minimum accident cost.

5.5.1 Unconstrained Optimization

Table 21 breaks down the results from the unconstrained optimization of the objective function found using Fminunc optimization solver in MatLab.

Table 21. Solution table for the various starting points (injury level, impact location) when unconstrained.

Minimization						Maximization					
Start Point		Optimized Solution				Start Point		Optimized Solution			
Injury Severity	Impact Location	Injury Severity	Impact Location	Cost ([$])	Iterations	Injury Severity	Impact Location	Injury Severity	Impact Location	Cost ([$])	Iterations
0	1	0.4	1.7	12,182.62	61	0	1	1.5	6.0	59,043.23	10
0	6	0.4	1.7	12,182.62	64	0	6	4.0	6.0	1,664,424.98	6
0	12	0.4	10.3	12,178.19	58	0	12	4.0	12.0	1,664,165.73	5
1	1	0.4	1.7	12,182.62	37	1	1	1.5	6.0	59,043.23	12
1	6	0.4	10.3	12,178.19	43	1	6	4.0	6.0	1,664,424.98	6
1	12	0.4	10.3	12,178.19	39	1	12	4.0	12.0	1,664,165.73	5
2	1	2.5	1.7	27,782.62	44	2	1	1.5	12.0	58,784.03	9
2	6	2.5	10.3	27,778.19	44	2	6	1.5	6.0	59,043.23	12
2	12	2.5	10.3	27,778.19	40	2	12	1.5	12.0	58,784.03	9
3	1	2.5	1.7	27,782.62	46	3	1	4.0	12.0	1,664,165.78	7
3	6	2.5	10.3	27,778.19	55	3	6	4.0	12.0	1,664,165.78	7
3	12	2.5	10.3	27,778.19	39	3	12	4.0	12.0	1,664,165.72	4
4	1	2.5	1.7	27,782.62	47	4	1	4.0	12.0	1,664,165.78	7
4	6	2.5	10.3	27,778.19	45	4	6	4.0	12.0	1,664,165.78	7
4	12	2.5	10.3	27,778.19	42	4	12	4.0	12.0	1,664,165.74	4

The maxima and minima were placed on the zone of impact diagram, Figure 24, to help visualize the solutions, shown in Figure 32. From this optimization it can be determined that the area where the higher initial cost should be directed is the front bumper zone of the FSLDPT. This could be done by redistributing existing costs or by adding additional up-front costs to the consumer. This will be discussed in a future work. These results are in line with the data about where the most common impact zone for the FSLDPT equipped with ADAS.

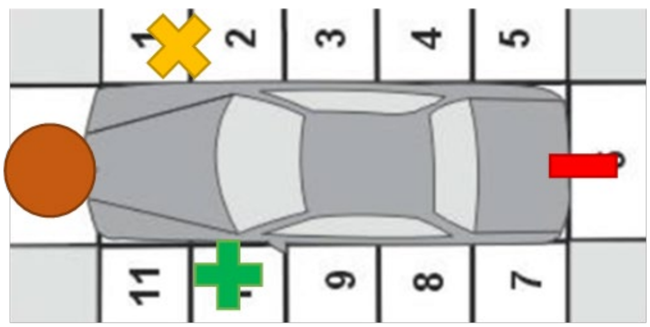

Figure 32. Highest accident cost is a dash in zone 6 with the second highest cost indicated as a circle in zone 12. Lowest accident cost is a plus in zone 10 with second lowest accident cost is an X in zone 1.

5.5.2 Constrained Optimization

The process to create Table 21 was repeated under the constrained condition of initial cost for the ADAS technologies of the six FSLDPTs. While Table 21 is the optimization of the surface in Figure 30, Figure 33 shows the optimization resulting locations established by the intersecting surfaces of each FSLDPT in Figure 31. The results for the maximum cost of the accident make sense and matches to the results of the unconstrained optimization. What was interesting was the location for the minima, visually depicted in Figure 33. The minima occur in zones 1, 3, 6, 8, and 10 depending on the FSLDPT. It is important to remember that the costs for each zone are solely based on the cost of the ADAS technologies.

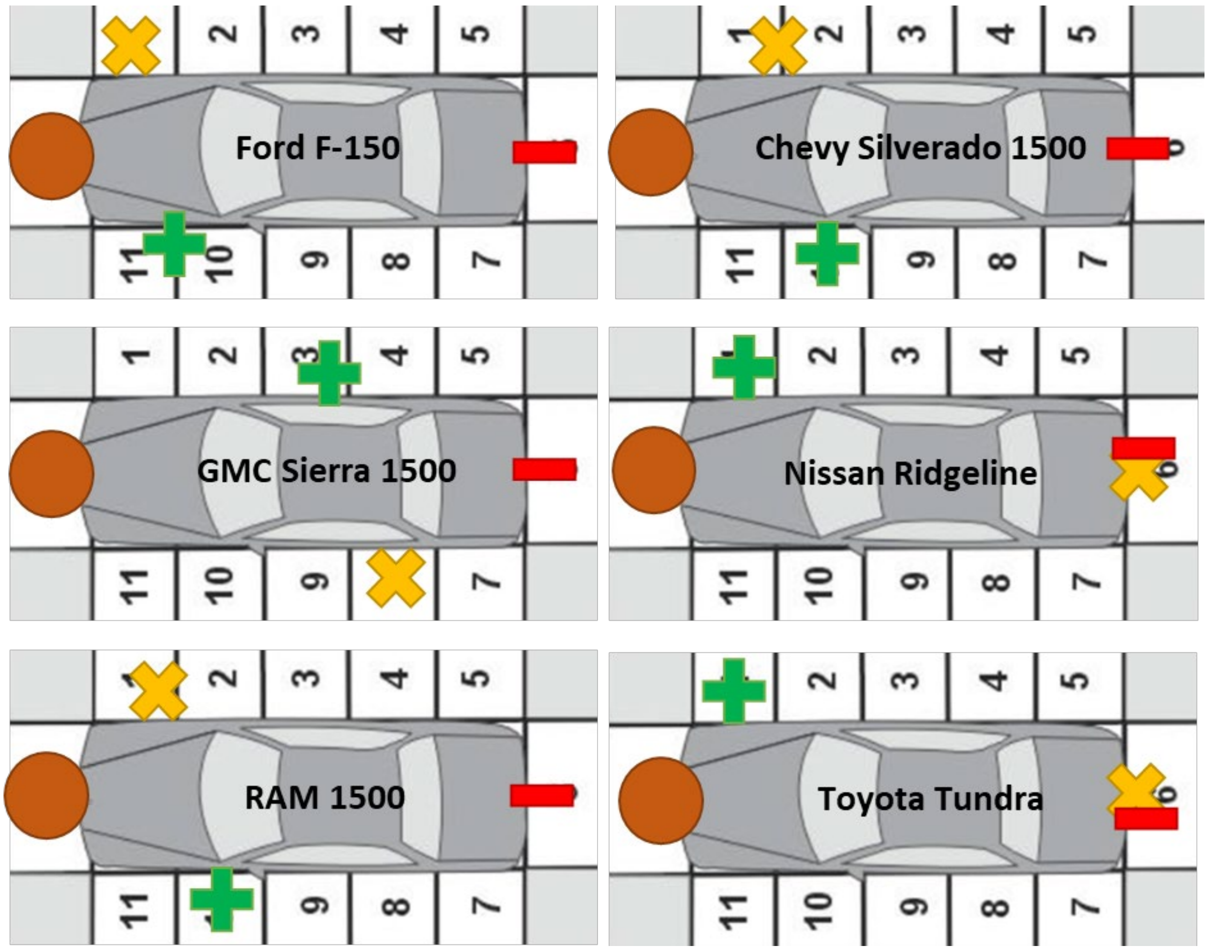

Figure 33. Constrained optimization results for the six FSLDPTs. Highest accident cost location is a dash with the second highest cost indicated as a circle and the lowest accident cost is a plus with second lowest accident cost is an X.

The initial cost of zones with ADAS technologies for the constrained problem causes the least expensive zone for an accident to be located in a zone without ADAS due to the zones with ADAS acting as inflection point except in cases where the zone acts as a saddle point when the optimization is searching for local minimums This can be seen from Figure 27 for the six FSLDPTs. In (Fish and Bras 2021), the initial cost of ADAS constraint curve has the cost of zone 0 to be \$0, so the zones closest to zone 0 (i.e. 1) ended up being the cheapest. While that was a valid argument, the evaluation of this work set the value for zone 0 equal to zone 12 to prevent the possibility for artificial minimums, and this work still found zone 1 to be one of the best impact locations for minimum accident cost. There is not a perfect mirroring of the optimized locations depicted in Figure 33. This occurs because of how the optimization search algorithm solver in MatLab approaches the minima.

These findings allow manufacturers information about how they can redistribute their investments in the ADAS for the impact zones on their FSLDPTs. Each manufacturer can see where their max investment costs are located on the vehicle an determine if that zone matches to where they want it to be located such as at the front bumper where the majority of fatal crashes occur. The automotive manufacturers could decide that where they have made investments on technology are not the ideal zones and can redistribute the investment to other zones.

5.6 Discussion of Sustainability

5.6.1 Sustainability Findings

When evaluating the environmental sustainability of ADAS it can be bifurcated into (1) sustaining and preserving the health and well-being of occupants and (2) reduction in need to replace the vehicle or its components.

What is gained from the unconstrained optimization analysis is that for any vehicle the majority of accident costs is driven by occupant injury severity. By adding ADAS to prevent sever injury or death, the cost of the accident is greatly diminished. The overwhelming majority of fatal crashes occur is in zone 12 (NHTSA 2010-2018), which is the second highest cost zone on the vehicle for crashes. Materials and resources can be saved by redirecting their expenditure from other low cost areas, the sides of the vehicle, to the more severe crash prone region of zone 12. Zone 6 is another area of opportunity for reducing material expenditure. This zone does not need the amount of ADAS technology allocated to it as is currently being done. The resource from zone 6, the most expensive region for a crash, could be saved as this zone experiences 1/100th the fatal crashes as zone 12 (NHTSA 2010-2018). By reallocating how and where materials for ADAS are expended, human lives can be preserved which leads in turn to greater societal production as well as the reduction in vehicle repairs and replacements.

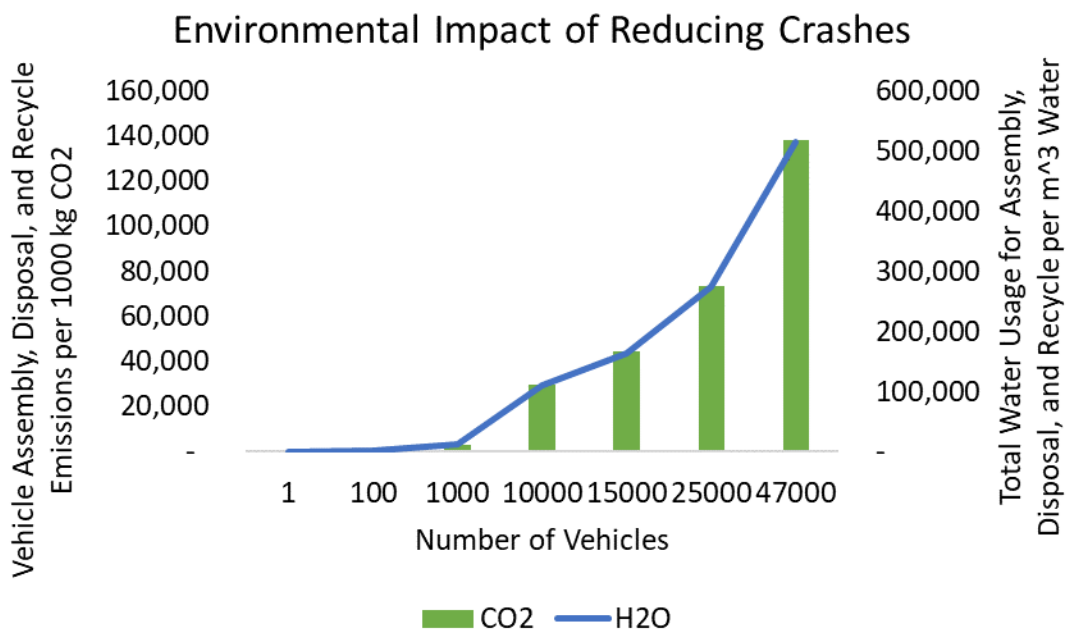

Figure 34. CO_2 and H_2O savings of preventing crashes of pickup trucks.

By reducing the number of crashes with significant damage the amount of CO_2 is produced as a byproduct of the manufacturing along with reductions in other material usage such as copper, zinc, steel, aluminum, and plastics. As shown in Figure 34 the amount of CO_2 and H_2O saved on a per vehicle basis, assumes average vehicle weighing EPA class 2 minimum of 6,001lbs (2722kg), is rather significant (Argonne National Laboratory 2020). Should ADAS reduce fatal crashes by the idealized 94% (47,000 vehicles) that would lead to a reduction in 138 million kg of CO_2 and 514,000 m^3 of water saved. A 30% (15,000 vehicles) reduction in fatal crashes due to ADAS would save 44 million kg of CO_2 and 164,000 m^3 of water. To provide perspective those are 205.6 and 65.6 Olympic size swimming pools of water respectively. Based on the findings of (Fish and Bras 2021) there appears to be a real-world reduction of fatal crashes for vehicles with effective ADAS between 70% and 93%.

5.6.2 Sustainability and Material Harvesting

While repairs play a lesser role in the cost outcome for accidents than injury cost, they do still contribute to other environmental impacts. When these systems are affected by a crash they at a bare minimum need to be recalibrated. Recalibration alone can cost $250-$300 USD as shown in Table 22.

Table 22. Expanded cost (USD) of repairing vehicle components (Association 2018, Preston 2020).

Part	Replacement	Min	Max
Front Bumper	Basic Bumper	700	1800
	Sensors	500	1900
	Recalibration	250	600
	Total	1450	4300
Headlights and Taillights	Halogen	200	500
	LED	750	1500
	Recalibration	100	250
	Total	300	1750
Windshield	Regular	300	500
	ADAS-capable	700	1500
	Sensors	800	1900
	Recalibration	250	250
	Total	1750	3650
Rear Bumper	Basic Bumper	700	1800
	Sensors	1000	2500
	Recalibration	250	250
	Total	1950	4550
Side Mirror	Regular	300	500
	ADAS-capable	1000	2500
	Recalibration	250	250
	Total	1250	2750

The sensors contain plastics and metals such as copper and zinc. Copper ore is harvested using underground and open cut mines (Northey, Haque et al. 2013). Once the ore is extracted it then needs to be processed. Preforming hydrometallurgical processing takes four stages:

- Mining – extraction of raw ore,

- leaching – reacting the ores with acid,
- solvent extraction – recovery process of the leached coppers into copper sulphate,
- and electrowinning – produces copper by using cathodes (Northey, Haque et al. 2013).

The lower the purity of the raw ore the greater amount of processing is required at each stage to refine the purity, thus leading to more by products. Zinc, which is often mined with lead is one of the largest contributors to heavy metal pollution in the environment (Zhang, Yang et al. 2012).

The use of plastics in the ADAS technologies is also a concern as not all plastics are recyclable. While thermoplastics are recyclable by reheating them and can be reused, thermosets are a single use plastic and are generally used in greater mass in automotive manufacturing (Schlechter 1994).

With all this in mind a cursory review of how much weight ADAS technologies contribute to the total vehicle weight. Out of 16 technologies commonly found on ADAS equipped vehicles (Automotive 2019), five (adaptive cruise control, lane keep assist, blind spot monitoring, semi-autonomous park assist, and back-up cameras) were looked at for third party parts across several vendors for gaining insight into the weight of the ADAS technologies. The total average weight of the five separate technologies was 7.2lbs (3.3kg) with a maximum weight of 10.5lbs (4.8kg) and a minimum weight of 4.3lbs (2.0kg). From this it can be inferred that a fully outfitted vehicle with ADAS could have anywhere between 13.8lbs (6.3kg) and 33.6lbs (15.2kg) of ADAS technology not including the wiring to connect the various ADAS technologies to the vehicle's computer.

5.6.3 Fuel Economy

Based on the added weight of the ADAS technologies to the vehicle, the fuel economy would be expected to be impacted, but due to the maximum weight only being 33.6lbs (15.2kg) essentially the weight of luggage the impact is very minimal. This is approximately 0.6% of the weight of the entire vehicle. Counter intuitively the shipping weights of the FSLDPTs with ADAS tended to weigh about the same to slightly less than there non-ADAS counter parts of the same trim level. This may have something to do with changes to allow the installation of ADAS technologies or it may be some other change unknown to the authors. In fact, based on fueleconomy.gov, the same trim level Ford F-150 with ADAS gets 17.0 mpg (7.2 kpl) versus the without ADAS getting 16.0 mpg (6.8 kpl) (United States Environmental Protection Agency). This leads to the question about newer more fuel-efficient vehicles entering the vehicle fleet will the current ADAS vehicles lead to environmental issues? As of now this is not a concern as they provide a safer driving experience than their non-ADAS counterparts leading to greater sustainability in preserving human life.

5.7 Future ADAS Design

When it comes to designing future ADAS technologies there are a few things that can be gained from this work. One option is to look at the costs of the technologies and redirect where the expenses for ADAS should be redistributed. From the optimization, the technology used for the ADAS in the rear of the Ford, Chevy, GMC, and RAM FSLDPTs, zones 6 and 12, have the potential for a reduction in the cost. Whether this reduction occurs in the form of restructuring the quality of the zones 6 and 12, the rear bumper and front bumper, ADAS technologies. This could be done through reducing the quality of the technologies present in those zones or the removal of certain technologies while improving other technologies in those zones. It can be debated on the need for zone 6 ADAS to be invested in as much as it currently is, since the data used to construct this optimization comes from fatal accidents. The utility of zone 6 would be more important for low severity cosmetic damage accidents. Zone 12 poses a different path for future designs. The most common zone to be involved with fatal accidents is zone 12, the front bumper, as shown in Figure 35.

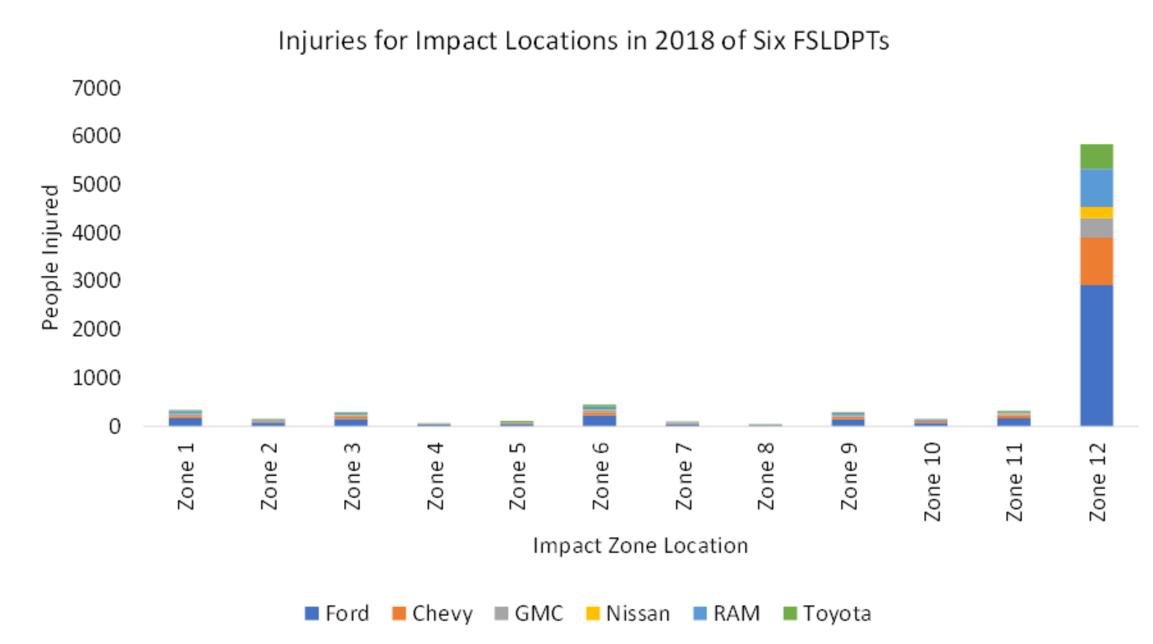

Figure 35. Accident impact locations for six FSLDPT in 2018 developed from NHTSA FARS data (NHTSA 2018).

For future designs of ADAS configurations, strong consideration for the best and worst impact areas should be taken into account. More emphases should be placed on the design of ADAS sensors located in zone 12. This zone is most often involved in accidents as shown in Figure 35. There are many factors involved in accidents and it is a simplification to assume that ADAS by itself can prevent accidents. With that said, automakers should improve certain zones of ADAS while halting and evaluating the necessity of other zones of ADAS. With the exception of zone 12, the other zones should be seen as lesser priorities for development and advancement of ADAS. These lesser priority zones provide convenience for the driver rather than substantively improved safety as seen by observing Figure 35, which is for both ADAS and non-ADAS. Which leads on to wonder how these systems could be adjusted to provide what is needed for convenience, while not exceeding those needs and becoming too costly. There are options here to either decrease the quality of the sensors, halt further development of ADAS in those zones, seek out different ADAS technologies, continue to improve ADAS in those zones blindly hoping for an improvement in safety, or stay the present course of ADAS development.

This chapter uses the Ford F-150, Chevy Silverado 1500, GMC Sierra 1500, RAM 1500, Nissan Ridgeline, and Toyota Tundra as its agents for study, but as previously stated these practices and principles could be applied to other vehicles. The values used to create Figure 27 for the cost of ADAS components could have been done for any individual vehicle or groups of vehicles.

5.8 Synopsis

Through the use of optimization for design improvements of FSLDPTs' ADAS it has been determined that zone 12, the front bumper, of the vehicle is ripe for continued improvement. Zone 6, the rear bumper, was found to be over developed for the level of safety that it provides in reducing accident injury severity. The other zones show there is not a need for improvement over their current standing. It is understood that these simulations were built on publicly available data for ADAS costs of associated with each of the specified FSLDPTs. That said, real damage costs from accidents may differ due to inclusion of other components of the vehicle such as the frame, the sheet metal, the tires, etc. It is also plausible that the automotive manufacturers have private details regarding the cost of the ADAS technologies in their respective FSLDPTs. Case in point, the Toyota and the Nissan did not have public data available for the cost of ADAS in zones 12 and 6, front and rear bumpers, respectively. It is a well know law that in the US all new vehicles now must have a rear camera, which would be an ADAS technology in zone 6. The sources for this research did not contain financial information about the aforementioned zone, and thus resulting in the exclusion of any cost for said zone when constructing the constraint equations for the Toyota and Nissan FSLDPTs. From the findings presented in this paper, automotive manufacturers can make informed financial decisions when developing and deploying ADAS technologies.

CHAPTER 6. A NEW PATH FORWARD: THE DEVELOPMENT OF BIOINSPIRED CONNECTED ADAS

There are a number of sources for connected ADAS as discussed in Chapter 2 section 3, but none have looked at how biological principles can be applied to ADAS. A number of ideas promoted for connected ADAS do have biological basis such as spacing of individuals while moving in groups (Yang, Liu et al. 2004, Kunze, Haberstroh et al. 2011, Yuan, Tasik et al. 2020). Even in this obvious instance of biological inspiration, no research has pointed to biology as a source of inspiration. Also, the protocols of how ADAS could be connected, proposed by others, lacks evaluation for biological inspiration. This research is the first to look to biology for inspiration for the connection of ADAS.

Biology has a number of analogous systems to automotive navigation. There are numerous instances of animals using landmarks, celestial navigation, and trail markings (Wehner and Menzel 1969, Hölldobler 1980, Chameron, Schatz et al. 1998, Menzel, Kirbach et al. 2011) similar in function to how the global position systems (GPS) or the Russian GLONASS operate. These can be thought of as far field communication for connected vehicles as GPS navigation systems in vehicles or on smartphones provide information about delays due to construction, traffic jams, and accidents. GPS navigation was included in the potential function tree for connected vehicle driving in chapter 3 because it links vehicles through a means of one way communication. In this manner, GPS acts as long-distance vehicle connectivity. This is great for improving travel times and the environmental impact of driving. While the far field connectivity of vehicles is important, the main focus of where this research intends to concentrate is on the near field connectivity of vehicles. The local communication of vehicles is important for crash prevention.

From the biology literature review a number of biological principles for how animals self-organize, communicate, and signal in the context of collision avoidance for group navigation became apparent. From this two main principles of biologically inspired connectivity – aposematism and bargaining – have been identified (West, Griffin et al. 2007, Caro and Allen 2017) as ways to improve vehicle crash avoidance through connected ADAS. While there are other biological inspirations found in Chapter 2 section 3, such as Leuckart's law and individual identifiable voices in a group, they function as mainly tertiary improvements to the two main principles.

6.1 Aposematism Connectivity for Vehicle Signaling

One manner to connect vehicles is through the use of systems that already exist on vehicles. All vehicles have an array of lights on the front and rear of the vehicle. The front of the has daytime running lights, low beams, high beams, and turn signals as standard on all vehicles with some having the addition of fog lamps. On the rear of the vehicle there are brake lights, backup lights, and turn signals as standard on all vehicles with some newer models now having rear fog lamps. These lights all have standardized meanings to drivers. For example, everyone is aware that the red lights on the rear of a vehicle means the car is braking when illuminated. The use of these lights is a means of communication among vehicles that already provides local connectivity. In most cases, the interpretation of these signals is left to the driver to interpret and accordingly react.

A growing population of vehicles are equipped with rear facing sensors. From the government mandated rear camera to other optional sensors such as reverse sensing systems or cross traffic alert, vehicles' ADAS is providing a detailed view of what is occurring to the rear of the vehicle. The instance of backing up or blind spot monitoring is currently the only times these ADAS systems are being put to use. Since most fatal crashes are associated with the front of the vehicle crashing into an object, it would be beneficial for these rearward facing systems to be able to communicate with the follow vehicle. If the vehicles were connected to each other, these systems on the lead vehicle could pass information to the follow vehicle if it is following too closely for the traveling speed.

From biology, aposematism – visual anti-predator signaling to the predator of a warning that attack will likely precipitate negative outcomes for the aggressor (Caro and Allen 2017) – provides an opportunity for how to connect vehicles. The infrastructure for doing this already exists on a large portion of vehicles. It would simply involve an inexpensive software upgrade to allow for vehicles to signal to prevent a crash from occurring similar to aposematism in biology for when a predator is nearby. By turning the rear sensors to actively monitor the rear of the vehicle, should another vehicle approach either too quickly or be following too closely the rear facing ADAS could visually signal the driver of the offending vehicle that they need to slow down and move away.

Visual signals are widely used in biology (Gross 2012, Heard-Booth and Kirk 2012, Hemelrijk and Hildenbrandt 2012, Chan and Gabbiani 2013, Benaragama and Gray 2014, Caro and Allen 2017, Sekar, Tapia et al. 2017, Farkas and Wang 2018) and are already being used in automobiles in the form of lights. By linking the ADAS technologies to the vehicle lights, which is achievable with just a minor software update, relay logic controller, and wiring, vehicle would have connected ADAS at a reasonably affordable level without the need for automotive manufacturers to make large investments in hardware or new technology. This could be achieved at several levels of connectivity from the simple case of the follow vehicle is too close so rear brake lights illuminate similar to a braking case. This would signal to the driver of the offending vehicle to slow down as visual signals in biology are better detected due to contrast or change over static patterns. It could also be distinct by having the light flash in a distinct pattern. It could be integrated with other ADAS systems to have the turn signal light illuminate to indicate changing lanes is a possibility. Figures 36 – 39 show potential lighting configurations for different signal for communicating to the follow vehicle.

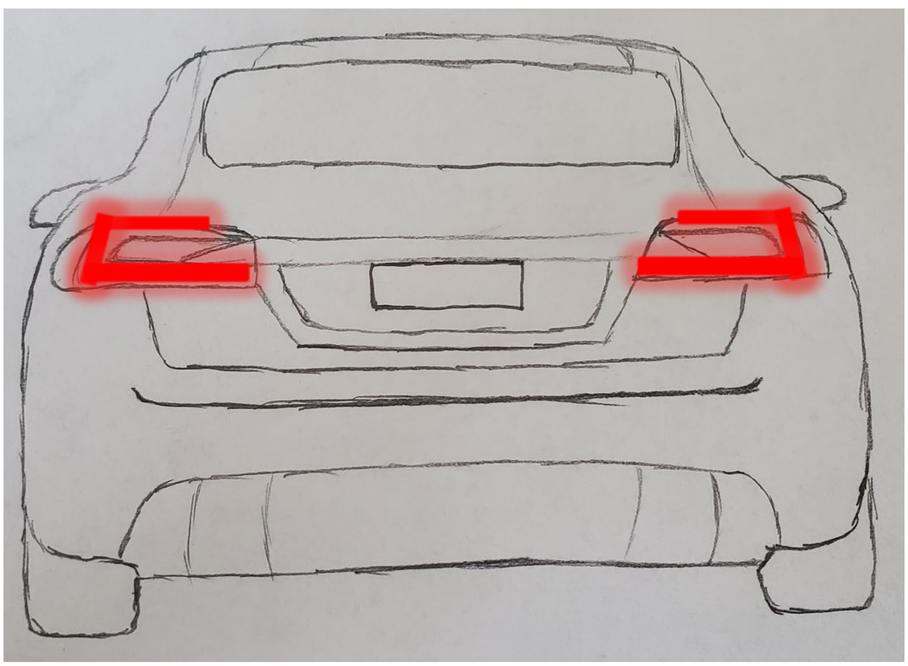

Figure 36. Slow down indicated by having the brake lights flash.

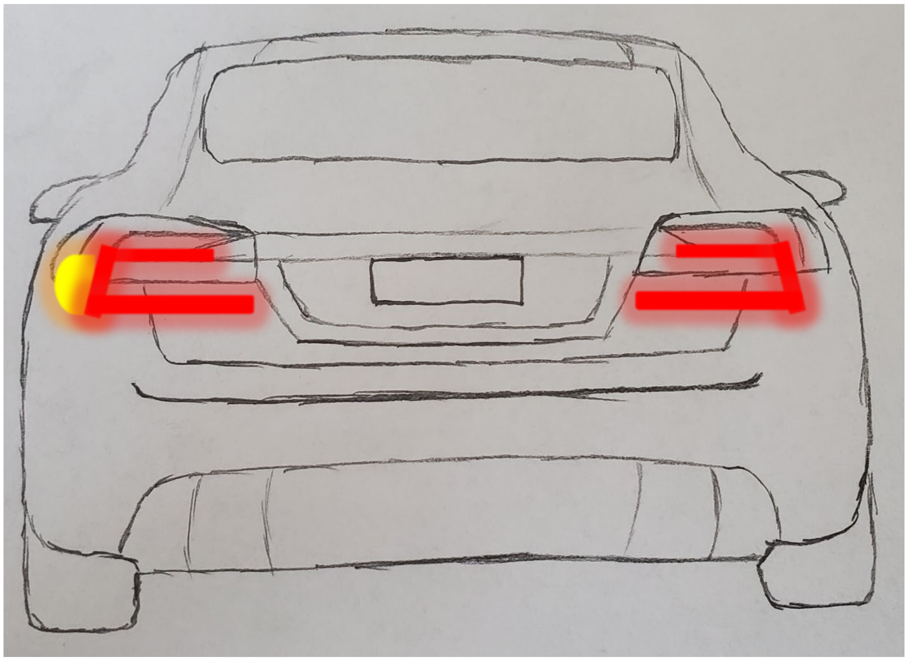

Figure 37. Slow down indicated by having the brake lights flash and the left turn signal solid to indicate that lane is available.

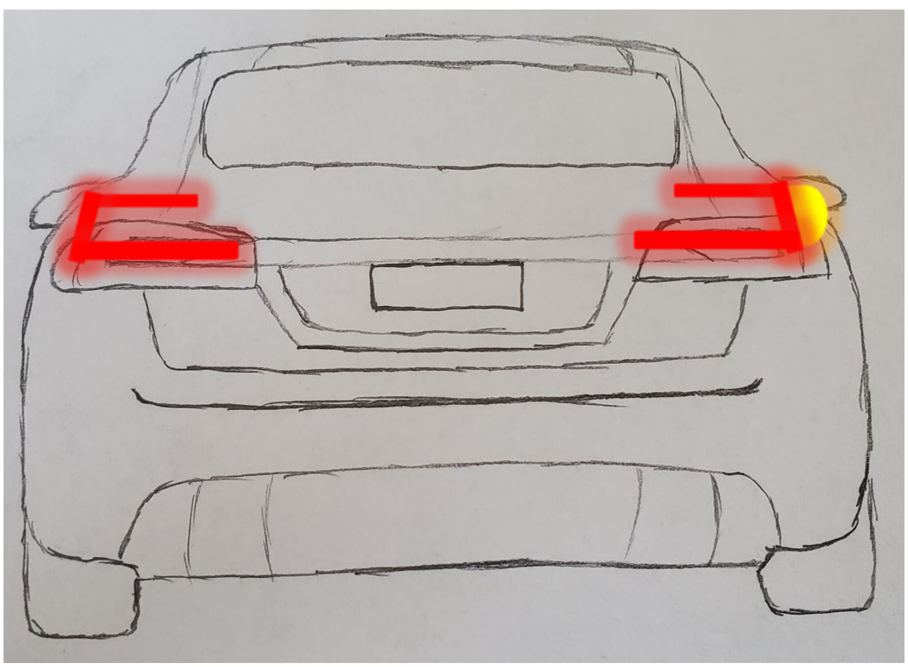

Figure 38. Slow down indicated by having the brake lights flash and the right turn signal solid to indicate that lane is available.

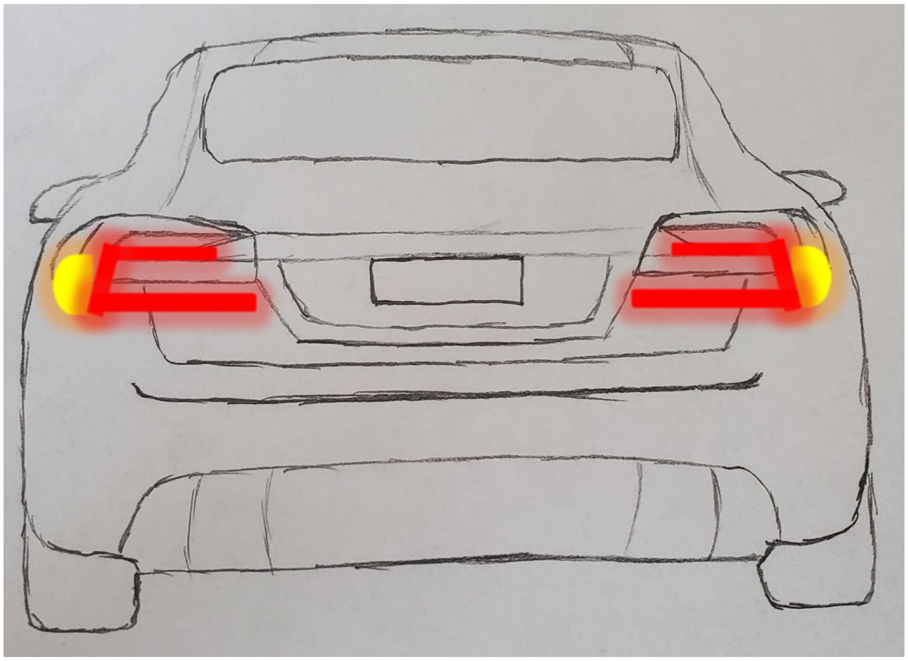

Figure 39. Slow down indicated by having the brake lights flash and the both turn signals solid to indicate that both right and left lanes are available.

While Figures 36 – 39 show how visual one-way communication could occur, Figures 40 – 43 demonstrate how this could be turned into two-way communication by having the follow vehicle use its front lights to send back visual signals to the driver of lead vehicle. This is also useful to have the signaling available on the front of the vehicle for instances of a front-to-front collision. These signals could be used to stop the vehicles or have them change lanes depending on the sophistication of the system and the availability of space to move. Having both front and rear signaling moves into the realm of connected vehicle bargaining.

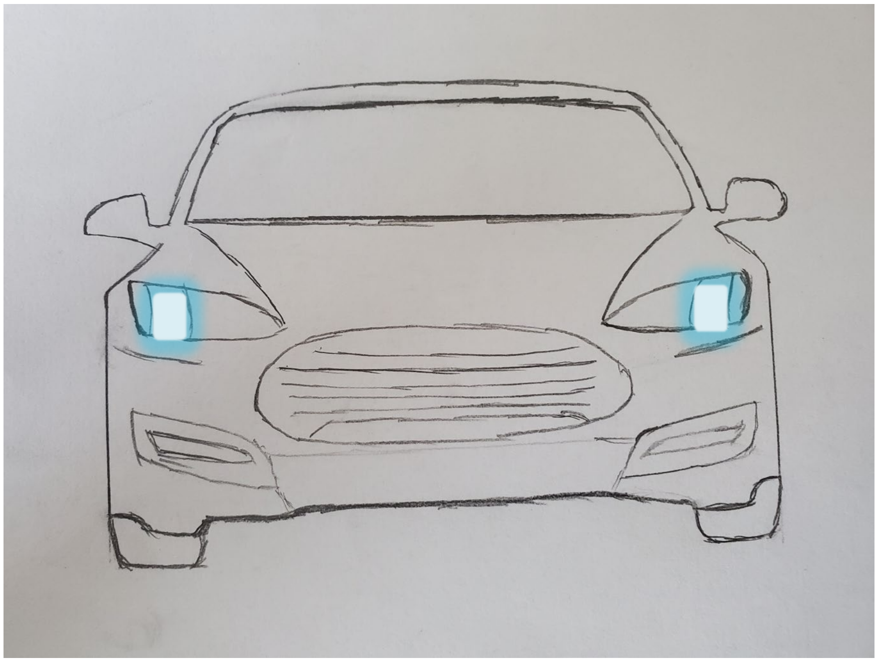

Figure 40. High beams flashing to signal they are too close to vehicle in front of them.

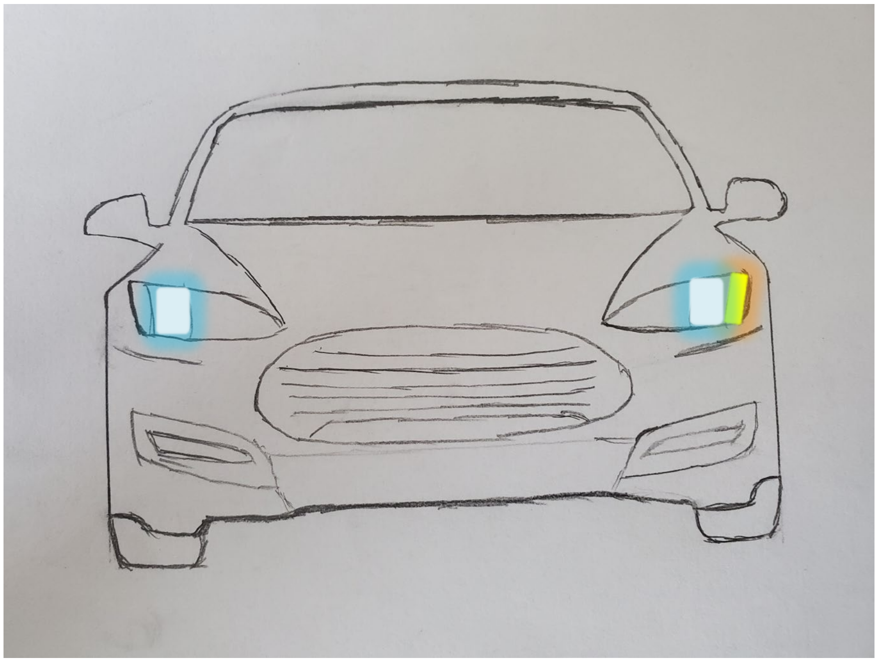

Figure 41. High beams flashing to signal they are too close to vehicle in front of them and left turn signal solid to indicate lane to left of driver is available.

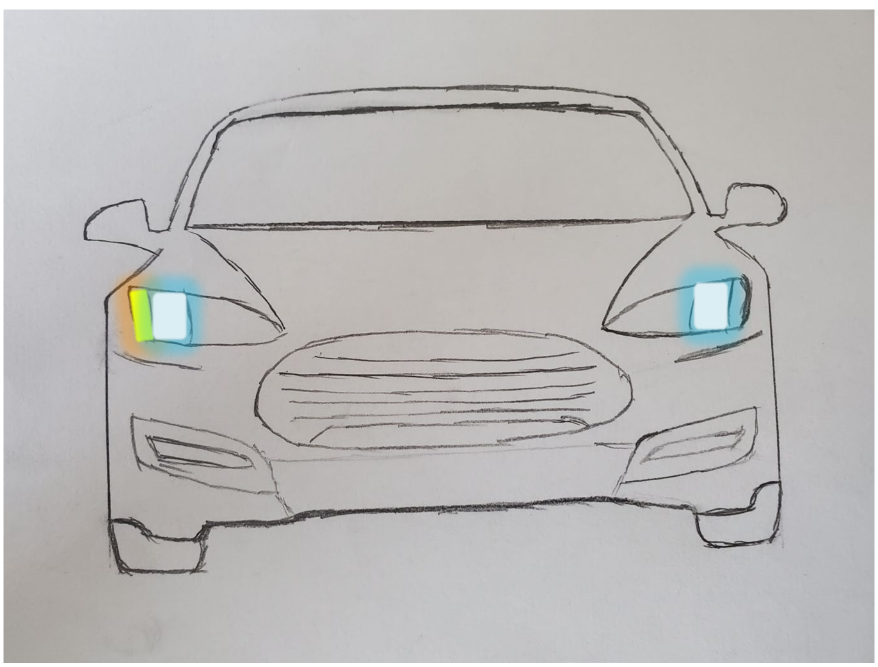

Figure 42. High beams flashing to signal they are too close to vehicle in front of them and right turn signal solid to indicate lane to right of driver is available.

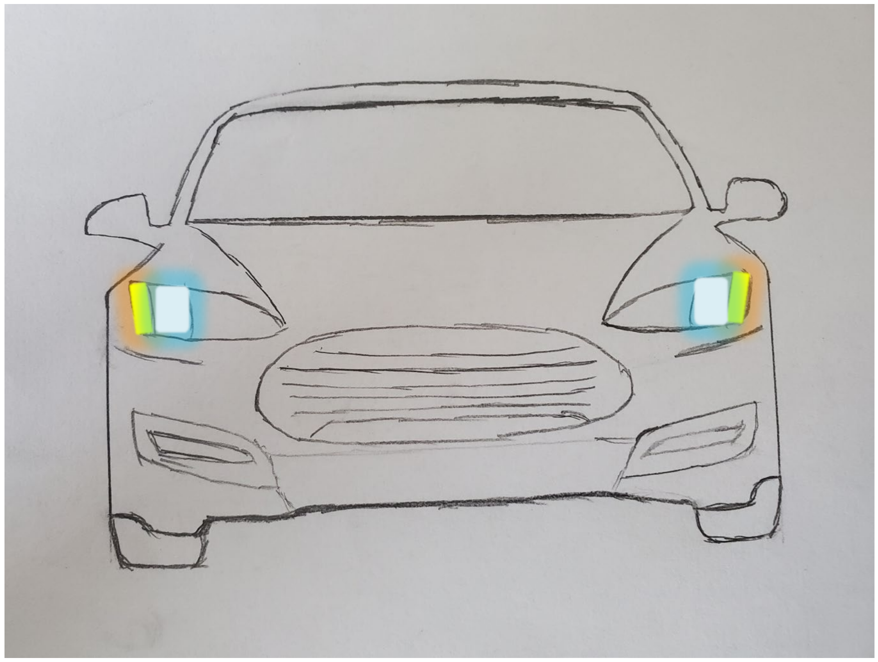

Figure 43. High beams flashing to signal they are too close to vehicle in front of them and both turn signal solid to indicate lanes to left and right of driver are available.

6.2 Connected Vehicle Bargaining

In nature social animals often bargain over resources for the good of the group (Ross-Gillespie and Griffin 2007, West, Griffin et al. 2007). This principle of bargaining has been applied in many fields of work, most notably economics (Nash 1950). By applying the principle of bargaining to connected vehicles optimal outcomes can be achieved for crash avoidance.

6.2.1 Generally Applied Connected Vehicle Bargaining

In the general case of having vehicles bargain with each other, certain information will need to be passed between vehicles in order to achieve the desired outcome of collision avoidance. With that said, as noted in biology error in transmission of signals does occur

(Lee, Ward et al. 2017). To mitigate against signal error which occurs in biology, the vehicle should initially act in a greedy fashion, doing what is best for the safety of the individual vehicle, to overcome this limitation. Then once communication is established and best course of action is determined, the individual vehicles should bargain and do what is best for the group.

By acting in this manner, this applies a type of redundancy for the conditions where connectivity cannot be established both ways. In Chapter 3, three pairings for the smart-vehicle were established – smart to smart, smart to semi-smart, and smart to dumb. An expanded listing of pairings:

- Smart to smart,
- Smart to semi-smart,
- Smart to dumb,
- Semi-smart to semi-smart,
- Semi-smart to dumb,
- and dumb to dumb.

A breakdown of how the three main pairings (smart to smart, smart to semi-smart, and smart to dumb) interact is shown in Figure 10 in Chapter 3 section 2. By having the smart-vehicle act in a manner that is best for its safety first and then acting in the best interest of the pairing, the smart-vehicle insulates itself against the possibility of doing what is best for the group while the other vehicle persists in its trajectory for a collision. Thus, this would lead to a crash if the smart-vehicle were not to act in its best interest firsts. In cases where connectivity cannot be established traditional ADAS technologies would act as a last line of defence as they do presently.

Once the smart to smart connection is established, what should be communicated is the next important step for determining the best outcome for the pairing of vehicles. Here a mainly physics/dynamics-based optimization will lead to the best outcomes. Another characteristic that some vehicles would transmit would be if they were an emergency vehicle. By including this emergency vehicle status in the connectivity transmissions, a ranked order priority can be established. This higher priority rank for emergency vehicles gives the emergency vehicles the ability to keep moving and avoid the need to slow down especially when time is a critical factor for their mission, be it an ambulance, fire truck, or police cruiser.

Of course other factors, can be obtained from other sensors on the smart-vehicle, such as road conditions and if other lanes are available for the vehicle to move. The smart-vehicles would exchange information about their respective weights, velocities, and relative positions for use in the optimization.

There are two main ways to determine if a crash has the potential to occur. One is directly determine the position, velocity, and acceleration of the vehicles involved and determine if they will intersect with each other, thus resulting in a crash. The other is to establish fields in front and behind the smart-vehicle based on its own travel velocity. If these fields are violated by another vehicle then the smart-vehicle responds through the established process of first moving to the safest location before bargaining to a more optimal location. In either of these cases they will be governed in some manner by

Equations 16 – 20. The α, F, m, t, x, v in Equations 16 – 19 are for acceleration, force, mass, time, distance, and velocity respectively. Denominations of subscript 0 indicate an initial value. For Equation 16, the equation means that the final velocity is equal to the initial velocity plus the acceleration multiplied by time. Since acceleration is the derivative of velocity with respect to time, Equation 16 is really the final velocity is equal to the initial velocity plus the change in velocity. For Equation 17, is developed by transforming t based on the definition of acceleration previously mentioned. Equation 18 is from the definition of velocity being the derivative of position with respect to time, so multiplying the velocity by time yields the final position. Equation 19 is developed by combining Equations 16 and 18 and using the definitions for velocity and acceleration. Equation 20 is Newton's second law of motion.

$$v = v_0 + at \tag{16}$$

$$v^2 = {v_0}^2 + 2a(x - x_0) \tag{17}$$

$$x = vt \tag{18}$$

$$x = x_0 + v_0 t + \frac{1}{2}at^2 \tag{19}$$

$$F = ma \tag{20}$$

Equations 16 – 20 were used to develop the optimization code found in Appendix C. The equations were also used for the analytics evaluation of the proposed biologically inspired connected system. The testing and evaluation of the system will be discussed in Chapter 7.

6.2.1.1 Design of the Optimization of Connected Vehicles

Two main approaches, Archimedean (goal weighting) and Lexicographic (rank ordering) optimums, immediately spring forth as possible approaches for finding the optimized solution for both vehicles. Finding the Archimedean optimum is achieved by weighting the values of each goal in a set and comparing the set values, and finding the Lexicographic optimum is found by comparing a hierarchy of goals from different sets. Both approaches are useful for assigning a hierarchy of importance to goals. Other approaches such as mapping the goals to the criterion space can be done to find the best possible outcome.

The objective is to minimize automotive crashes. The goals are to maintain at least a safe distance between vehicles, to have as low of a change in acceleration felt by the vehicle occupants, and to not impede the travel of emergency vehicles (police cruisers, ambulances, and fire trucks). In the case where the vehicle's weight is only as detailed as to which EPA weight class it belongs, a lexicographic approach may be preferable for finding the objective.

For the design of the vehicle model, there are a number of given variables:

- Initial speed of vehicles: v_1 & v_2,
- Emergency vehicle status of vehicles: e_1 & e_2,
- Distance between vehicles: d.

These givens would be obtained through a communication protocol discussed in section 6.3. The objective function for this problem is shown in Equation 21. Where $\bar{x}$ is an array of input variables. The weights assigned to each part of the objective function were 0.6 for the emergency vehicle function, 0.3 for the maintaining at least a minimum safe follow distance function, and 0.1 for the minimum acceleration felt by occupants function.

$$min\big(F(\bar{x})\big) = 0.6\,E(\bar{e}) + 0.3\,D\big(\bar{v}, \bar{d}\big) + \;0.1\,A(\bar{v}) \tag{21}$$

This objective function is subject to the constraint Equations 22 – 23. Equation 22 is based on what the standard vehicle's max acceleration is able to achieve before loss of control (Sawicki 2016). This could be different for higher-end vehicles such as luxury sports cars (i.e. BMW M3, Toyota Celica GT, etc.).

$$a \leq 4.6\ {}^{m}\!/_{s^2} \tag{22}$$

$$\Delta v\ \leq \frac{d}{t} \tag{23}$$

The constraint equations were developed from particle physics and dynamics Equations 16 – 20. Since the acceleration in Equation 22 is limited to a max of 4.6 m/s^2 based on (Sawicki 2016), there is not a need to know the mass of each vehicle. A more complex model could be developed that uses the mass of the vehicles to determine what the upper limit for acceleration could be for a specific vehicle.

A common rule for following distance (d in Equation 23) is three seconds behind the lead vehicle (Driving Test Success 2020). Table 23 breaks down following distances for common travel speeds in the US.

Table 23. Safe following distances for common speeds in the US.

Travel Speed		Following Distance		Common Locations of Speeds Used for Roads in the US
[mph]	[kph]	[Meters]	[Yards]	
10	16	13	14	Parking lot speed
25	40	34	37	Residential areas
35	56	47	51	Urban 4-lane roads
45	72	60	66	Urban highway
55	89	74	81	County highway
65	105	87	95	Interstate highways
80	129	107	117	Max speed limit in US
140	225	188	206	Max speed of US vehicles

The objective is the find the min(E, V, A). E is the emergency vehicle status. V is the change in the vehicles' velocities, and A is the acceleration of the vehicles involved. Table 24 breaks out the givens, find, objectives, and assumptions. Simplifications were made for the problem such as setting the maximum acceleration change to a constant value rather than compute it based on the mass of the vehicles. In Table 23, 1 and 2 are for the two vehicles involved, and i and f are for initial and final values. In Table 23 a, d, e, and v are for acceleration, distance, emergency vehicle status, and velocity.

Table 24. Givens, find, objectives, and assumptions for the development of the connected vehicle bargaining problem.

Givens	**Find**	**Objectives**	**Assumptions**
v_{1i} & v_{2i}	v_{1f} & v_{2f}	min(E)	$a_i \leq 4.6$ m/s^2
e_1 & e_2	a_1 & a_2	min(V)	t = 3s for a safe stop
d_i		min(A)	

The optimization code for connected vehicle bargaining can be found in Appendix C. Chapter 7 discusses the results of the optimization as well as the analytics of biologically inspired advanced driver assistance systems.

6.2.2 Connected Vehicle Bargaining for the Aposematism Condition

For the case of connecting vehicles based on Aposematism in animals, vehicles can bargain using signalling from their lights as discussed previously. This mode does limit the amount of information transferable between the vehicles. Instead of sending weight, velocity, relative position, and emergency vehicle status (if applicable), the vehicles could only transfer a weight range in the form of light flashing frequency and if they are smart-vehicles (based on their ability to respond to signals). Limiting what data is transferred between vehicles would assist in computation time for quicker action to be taken by the BICADAS equipped vehicle. The weight ranges would be based on EPA weight classes. This would allow for relative weight comparisons to be used by the optimization program discussed in section 6.2.1.1. The other information such as the velocity would need to me gained by use of other sensors on the vehicles. As discussed previously the smart-vehicles would move to the safest position for them until confirmation of the other vehicle also being smart is detected. This detection could be done through the use of the vehicle's cameras.

In terms of the aposematism signalling, there are again the three cases: smart to smart, smart to semi-smart, and smart to dumb. In the case of smart to smart, both vehicles would use their lights to indicate to each other based on the pre-described patterns. Once the signals have been transmitted by the lights and received by the camera sensors, the vehicles would move according to the optimized plan for the grouping. In the second case of smart to semi-smart, the semi-smart vehicle would be able to send signals, but it would be unable to automatically act on the information transferred. It would be beneficial for the semi-smart vehicle in that should another vehicle become likely to collide with it, it can signal the other vehicle. In the case of the other vehicle being a smart vehicle, it can take action, and in the case of a dumb vehicle, the light signals from the smart vehicle can still signal the dumb vehicle's driver of the impending collision. In the other case of smart to dumb, the smart vehicle would transmit the signals and there would be no visual response by the dumb vehicle. The advantage here is the light signalling could be seen by the dumb vehicle's driver who could react accordingly.

6.3 Means of Connecting Vehicles

Driver reaction takes between 0.7s and 1.5s, which leads to an accordion effect for vehicles (Yang, Liu et al. 2004) even when crashes are avoided. Having smart vehicles connected would avoid this accordion effect and lead to better traffic flow and fewer crashes. There are many ways vehicles could be connected for V2V communication. The optimized connected vehicle protocol outlined in section 6.2.1.1 could be applied through many different means of V2V communication. There are a number of communication protocols that already exist that could be adapted or are already in place for V2V communication. Table 25 is of a several protocols that could be used for V2V communication with their theoretical maximum range and data transfer rates.

Table 25. Communication protocols that could be used for V2V communication.

Protocol	Max Range	Max Throughput	References
DSRC	1000m	54 Mbps	(Yang, Liu et al. 2004, Hafner, Cunningham et al. 2013, Johansen and Løvland 2015, Tsugawa, Jeschke et al. 2016, Kukkala, Tunnell et al. 2018)
DGPS	Global	57.6 kbps	(Meng, Wevers et al. 2004, Yang, Liu et al. 2004, Hafner, Cunningham et al. 2013, Johansen and Løvland 2015, Sun, Vianney et al. 2020)
VANETs	200m	11 Mbps	(Chuah and Fu 2006, Yuan, Tasik et al. 2020)

MANETs	250m	2 Mbps	(Nadeem, Dashtinezhad et al. 2004, Sawhney and Vohra 2012)
Wi-Fi	90m	2.4 Gbps	(Mitchell 2020)
3G	3000m	42 Mbps	(Kanchwala 2021, Rogerson and Kavanagh 2021)
4G	3000m	1 Gbps	(Kanchwala 2021, Rogerson and Kavanagh 2021)
5G	3000m	50 Gbps	(Kanchwala 2021, Rogerson and Kavanagh 2021)
VLC (LED)	2000m	500 Mbps	(Siemens 2012)

It is important to point out that 3G, 4G, and 5G all have to travel from the vehicle to a tower and then to the other vehicle for information communication, which effectively halves the data max throughputs to 21Mbps, 500Mbps, and 25Gbps respectively. With that said Table 25 can be plotted to visually represent how the different communication protocols perform relative to each other as shown in Figure 44. The DSRC was a protocol set aside by the US government for V2V communication in the early 2000s. If the DSRC is used as a standard for comparison of the other communication protocols, 4G, 5G, VLC, and Wi-Fi all have greater data throughput rates with 3G being slightly below the DSRC. With respect to range, 3G, 4G, 5G, VLC, and DGPS have greater range that they are effective over than the DSRC. Between the two parameters only 4G, 5G, and VLC meet or exceed the threshold set by the DSRC. Of the three communication protocols that can outperform the DSRC protocol, VLC uses visual light for its communication and would be the most adaptable to the aposematism connectivity case detailed in this chapter. It does have the downside of being affected during deprecated visual conditions such as rain or snow as well as when line of sight is obstructed such as by a hill.

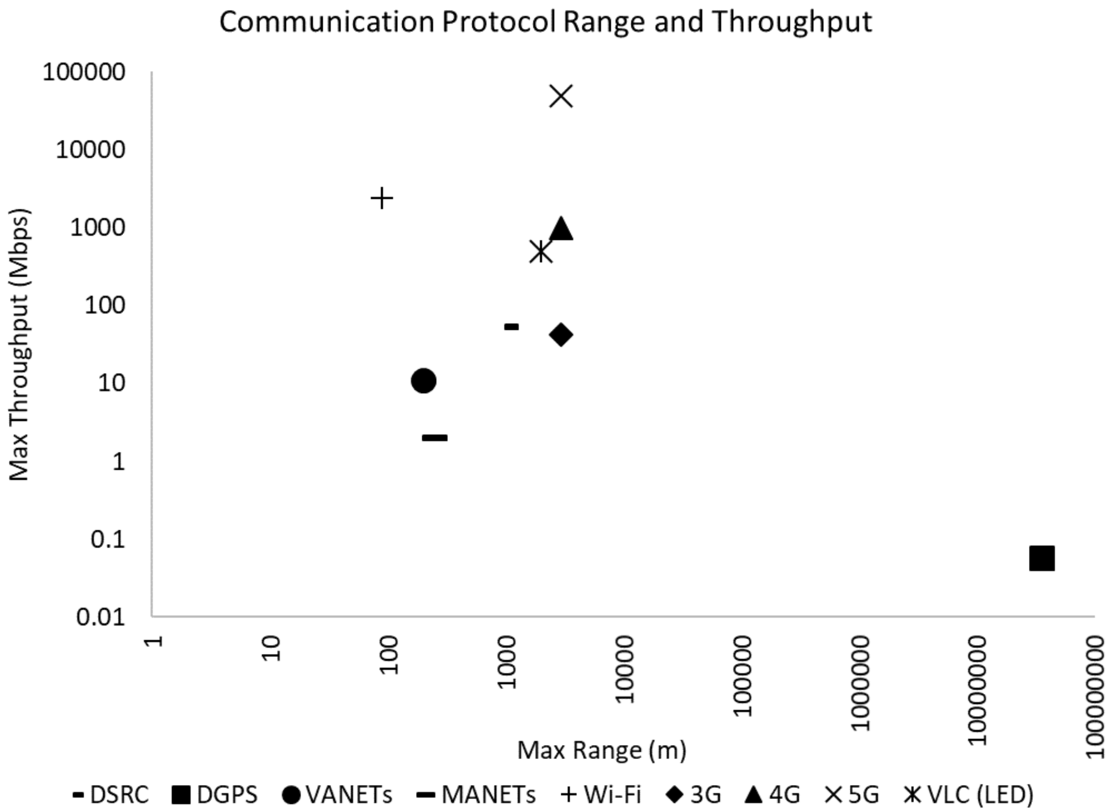

Figure 44. Range throughput plot of different potential V2V communication protocols.

Using VLC to communicate and connect vehicles the flow diagram in Figure 10 could be updated as shown in Figure 45. In doing so even the smart to dumb and smart to semi-smart cases would have an improvement over traditional ADAS because of the lights provide visual signals that the drivers of the non-BICADAS (smart vehicles) to observe and react upon themselves.

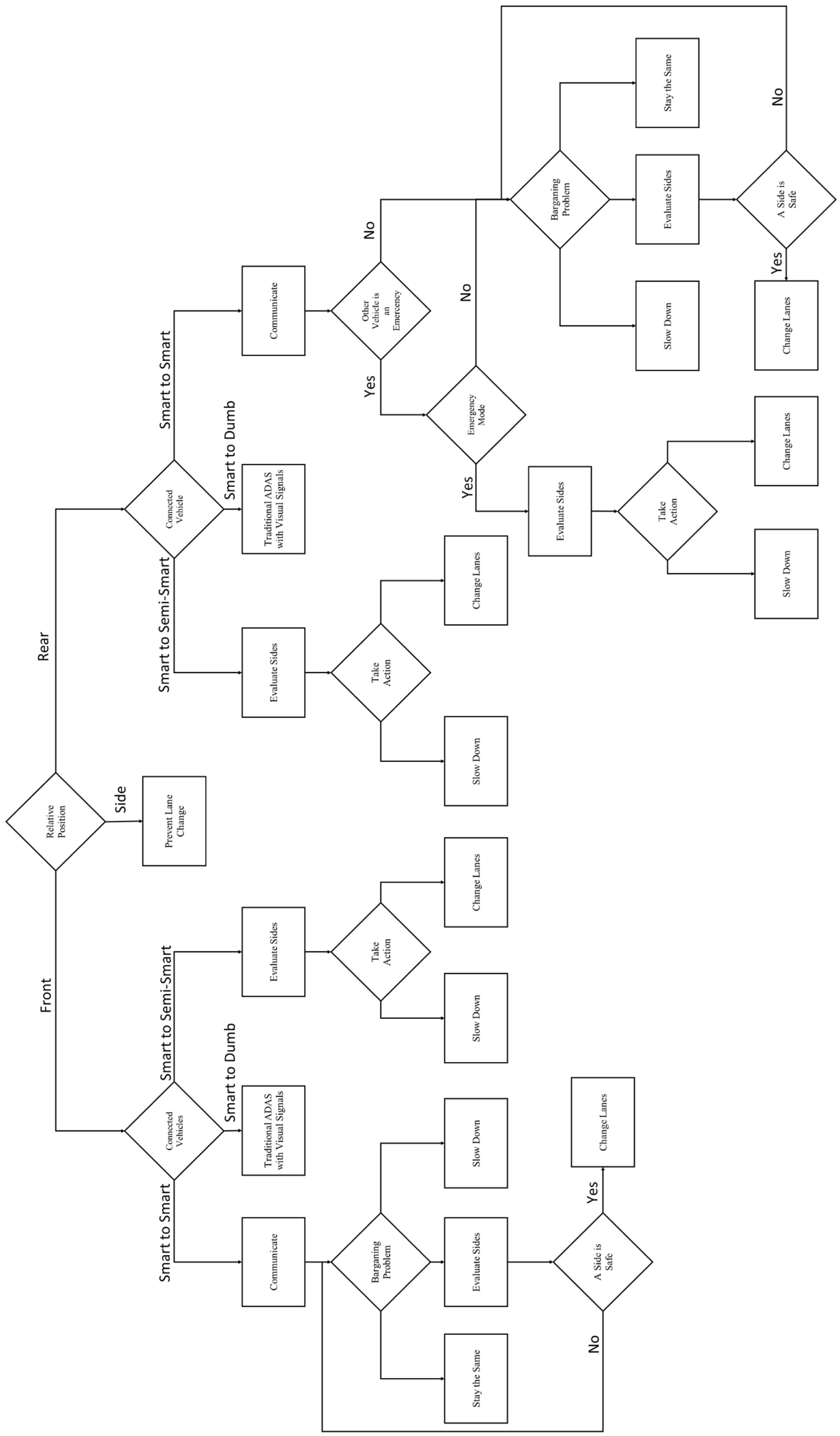

Figure 45. Logic flow diagram for determining how BICADAS equipped vehicles using VLC interact with other vehicles.

CHAPTER 7. TESTING OF THE BIOINSPIRED CONNECTED ADAS

The evaluation of the biologically inspired connected advanced driver assistance systems (BICADAS) can be achieved in two main manners. The first is to evaluate BICADAS from a pure physics and dynamics perspective. Doing so can evaluate the theoretical potential BICADAS can provide for vehicle accident prevention. The second means of evaluation is to analyze the optimization that was described in section 6.2.1.1 and whose code is available in Appendix C. This will provide an idea about how these systems could interact in a practical manner.

7.1 Analytical Evaluation of Biologically Inspired Connected ADAS

It is important to recognize that there are a number of viable communication protocols that meet or exceed the established DSRC communication bandwidth setup by the government for the purpose of V2X communication. These communication protocols were shown in Figure 44 and a view of the communication protocols that exceed the minimum requirements of the DSRC capabilities are shown again in Figure 46 in a zoomed in view.

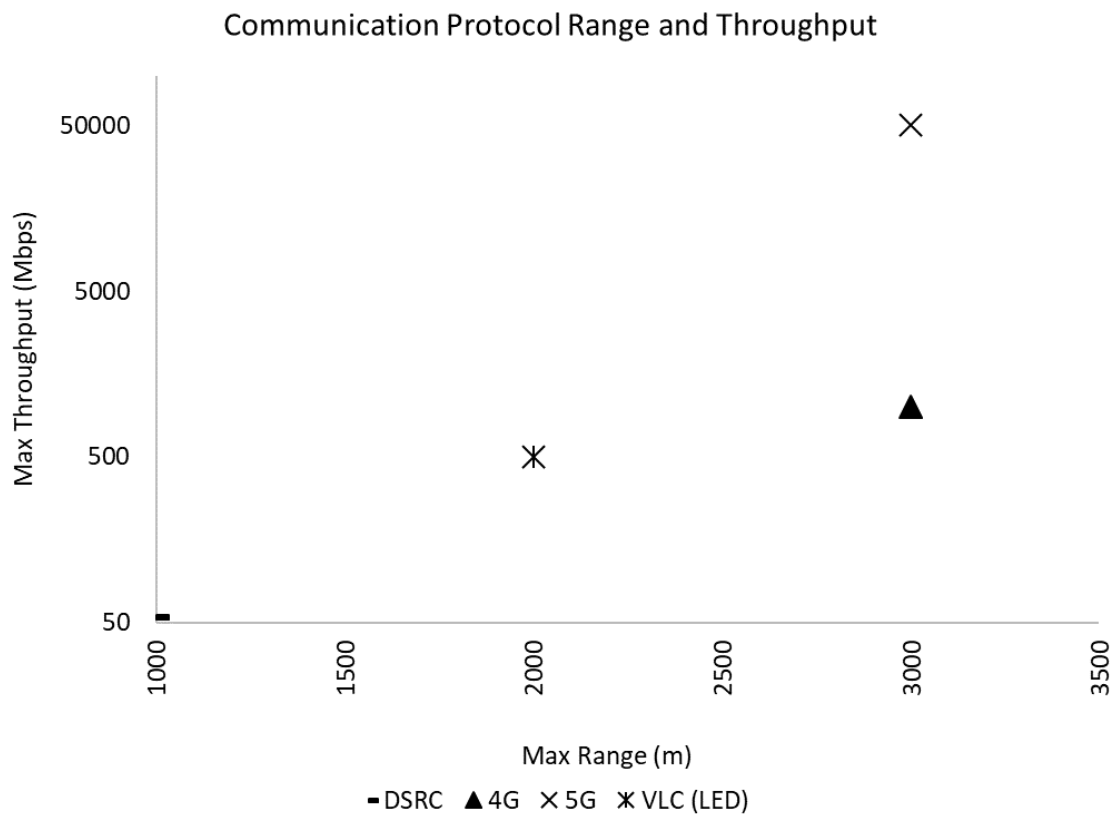

Figure 46. Communication Protocols that surpass the established DSRC.

Of the three protocols for communication (4G, 5G, and VLC) shown in Figure 46 that surpass the minimum viability established by the DSRC communication protocol, only the VLC is a direct link between the two vehicles. 4G and 5G must first pass to a communication tower during their transfers of information. As such the max through puts for 4G and 5G would be effectively halved as shown in Figure 47. Even when halved for throughput both still outperform the DSRC communication protocol. 4G halved and VLC now both have a max throughput of 500 Mbps, while 5G halved is 2500 Mbps. For the reader, Figures 46 and 47 have different scales for their X- and Y-axes than Figure 46. Figure 46 has a log-log axes whereas Figures 46 and 47 have a log scale Y-axis and a linear X-axis with the origin set to (1000, 50) verses an origin of (1, 0.01) in Figure 46.

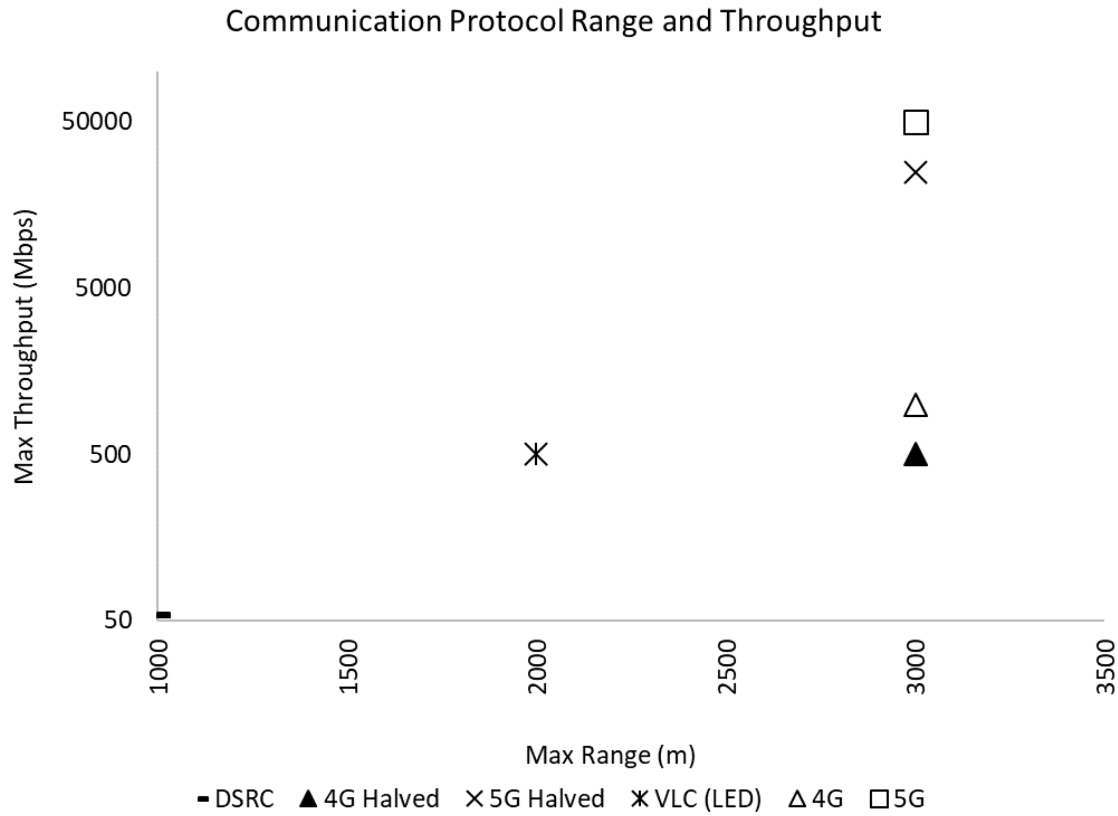

Figure 47. Communication Protocols that surpass the established DSRC with 4G and 5G halved.

The analytical evaluation of BICADAS is based on the principles governing physics and dynamics of bodies. In some instances, bodies can be simplified to particle physics for evaluation. In either case, the evaluation will be mainly conscribed to Equations 16 – 20 which are reproduced here.

$$v = v_0 + at \tag{16}$$

$$v^2 = {v_0}^2 + 2a(x - x_0) \tag{17}$$

$$x = vt \tag{18}$$

$$x = x_0 + v_0 t + \frac{1}{2} a t^2 \quad (19)$$

$$F = ma \quad (20)$$

There are two main scenarios that are seen in the NHTSA FARS datasets for vehicle-on-vehicle crashes. The first is front bumper on front bumper as shown in Figure 48, and the second is front bumper to rear bumper as shown in Figure 49. It again is worth mentioning that FARS only contains data about vehicles involved in crashes that resulted in a fatality, but it is reasonable to believe these two types of crashes result in non-fatal crashes as well. Essentially if it can avoid the most extreme scenario, a fatal crash, it will avoid more minor crashes, non-fatal, as well.

Figure 48. Front bumper on front bumper crash.

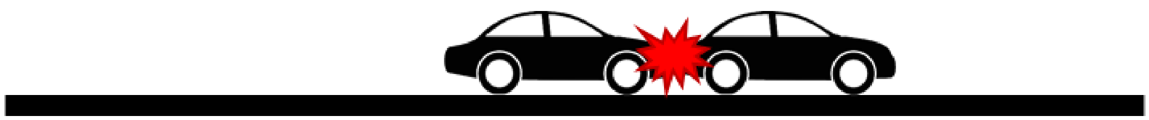

Figure 49. Front bumper on rear bumper crash.

7.1.1 Front Bumper to Front Bumper Collision

In the case depicted in Figure 48 (front bumper on front bumper), one of the vehicles would need to change lanes preferably to a lane situated to the right of the driver. Should that option not be available immediately, both vehicles will need to slowdown. This slowdown could lead to both vehicles braking should neither be afforded the opportunity to change lanes. Most vehicles can comfortably accelerate and decelerate at a rate of 4.6 m/s^2 (Sawicki 2016) and in emergency cases vehicles can brake with a max deceleration of 6.0 – 9.3 m/s^2 (Kudarauskas 2007). Max braking is calculated using Equations 24 and 25 which come from (Oppenheimer 1977, Kudarauskas 2007).

$$\alpha_{xn} = \varphi_x \cdot g \tag{24}$$

$$\alpha_{xn} \geq [0.1 + 0.85(\varphi_{x\,max} - 0.2)] \cdot g \tag{25}$$

Where α_{xn} is the deceleration of the vehicle, φ_x is the coefficient of longitudinal cohesion between the tires of the vehicle and the ground (dry asphalt: $\varphi_x = 0.8$), and g is the acceleration due to gravity (9.81 m/s^2).

Figure 50. Two vehicles facing impending front bumper to front bumper collision.

Based on Equation 17 under the condition show in Figure 50, Table 26 was developed where both vehicles are moving towards each other at the same velocities and cannot change lanes. When acceleration is greater than or equal to -4.6 m/s^2 the vehicles can both easily brake to avoid crashing into each other. For accelerations less than -4.6 m/s^2 and greater than or equal to -9.3 m/s^2, are shown in orange in Table 26 and represent emergency braking to avoid collision, but still do not crash into each other. For accelerations less than -9.3 m/s^2, are shown in red in Table 26 and represent that even with emergency braking a crash will still occur. Again, Table 26 assumes that there is no possibility of either vehicle moving out of the other vehicle's way by changing lanes, and both vehicles are moving in opposite directions at the same initial velocities.

Table 26. Head on impending collision avoidability by braking showing decelerations achieved by the proposed BICADAS technology.

Initial Distance	Initial Velocities		Final Velocities		Acceleration Change
(m)	(mph)	(m/s)	(mph)	(m/s)	(m/s^2)
10	10	4.5	0	0	-2.0
20	10	4.5	0	0	-1.0
30	10	4.5	0	0	-0.7
40	10	4.5	0	0	-0.5
50	10	4.5	0	0	-0.4
20	25	11.2	0	0	-6.2
30	25	11.2	0	0	-4.2
40	25	11.2	0	0	-3.1
50	25	11.2	0	0	-2.5
60	25	11.2	0	0	-2.1
30	35	15.6	0	0	-8.2
40	35	15.6	0	0	-6.1
50	35	15.6	0	0	-4.9
60	35	15.6	0	0	-4.1
70	35	15.6	0	0	-3.5
40	45	20.1	0	0	-10.1
50	45	20.1	0	0	-8.1
60	45	20.1	0	0	-6.7
70	45	20.1	0	0	-5.8
80	45	20.1	0	0	-5.1
60	55	24.6	0	0	-10.1
70	55	24.6	0	0	-8.6
80	55	24.6	0	0	-7.6
90	55	24.6	0	0	-6.7
100	55	24.6	0	0	-6.0
70	65	29.1	0	0	-12.1
90	65	29.1	0	0	-9.4
110	65	29.1	0	0	-7.7
130	65	29.1	0	0	-6.5
150	65	29.1	0	0	-5.6
90	80	35.8	0	0	-14.2

Initial Distance (m)	Initial Velocities (mph)	(m/s)	Final Velocities (mph)	(m/s)	Acceleration Change (m/s^2)
110	80	35.8	0	0	-11.6
130	80	35.8	0	0	-9.8
150	80	35.8	0	0	-8.5
170	80	35.8	0	0	-7.5

Unlike the values in Table 26, which are the result of an immediate recognition that could only be achieved through the use of the proposed BICADAS technology, Table 27 represents what a human driver could achieve under the same conditions without the use of BICADAS assuming a 0.7 second reaction time to begin braking.

Table 27. Head on impending collision avoidability by braking showing decelerations achieved by a human with a 0.7 second reaction time.

Initial Distance (m)	Initial Velocities (mph)	(m/s)	Final Velocities (mph)	(m/s)	Acceleration Change (m/s^2)
10	10	4.5	0	0	-2.9
20	10	4.5	0	0	-1.2
30	10	4.5	0	0	-0.7
40	10	4.5	0	0	-0.5
50	10	4.5	0	0	-0.4
20	25	11.2	0	0	-10.3
30	25	11.2	0	0	-5.6
40	25	11.2	0	0	-3.9
50	25	11.2	0	0	-3.0
60	25	11.2	0	0	-2.4
30	35	15.6	0	0	-12.9
40	35	15.6	0	0	-8.4
50	35	15.6	0	0	-6.3
60	35	15.6	0	0	-5.0
70	35	15.6	0	0	-4.1
40	45	20.1	0	0	-15.6
50	45	20.1	0	0	-11.3
60	45	20.1	0	0	-8.8
70	45	20.1	0	0	-7.2
80	45	20.1	0	0	-6.1
60	55	24.6	0	0	-14.1

Initial Distance (m)	Initial Velocities (mph)	(m/s)	Final Velocities (mph)	(m/s)	Acceleration Change (m/s^2)
70	55	24.6	0	0	-11.5
80	55	24.6	0	0	-9.6
90	55	24.6	0	0	-8.3
100	55	24.6	0	0	-7.3
70	65	29.1	0	0	-17.0
90	65	29.1	0	0	-12.1
110	65	29.1	0	0	-9.4
130	65	29.1	0	0	-7.7
150	65	29.1	0	0	-6.5
90	80	35.8	0	0	-19.7
110	80	35.8	0	0	-15.1
130	80	35.8	0	0	-12.2
150	80	35.8	0	0	-10.2
170	80	35.8	0	0	-8.8

While Table 27 shows the results of the quicker reaction time while driving, the longer reaction time of a person to react while driving is 1.5 seconds, which is shown in Tale 28. In Table 28, the same scenario is played out as in Tables 26 and 27 just with the slower reaction time of 1.5 seconds by a human driver.

Table 28. Head on impending collision avoidability by braking showing decelerations achieved by a human with a 1.5 seconds reaction time.

Initial Distance (m)	Initial Velocities (mph)	(m/s)	Final Velocities (mph)	(m/s)	Acceleration Change (m/s^2)
10	10	4.5	0	0	-6.1
20	10	4.5	0	0	-1.5
30	10	4.5	0	0	-0.9
40	10	4.5	0	0	-0.6
50	10	4.5	0	0	-0.5
20	25	11.2	0	0	-38.6
30	25	11.2	0	0	-9.4
40	25	11.2	0	0	-5.4
50	25	11.2	0	0	-3.8
60	25	11.2	0	0	-2.9
30	35	15.6	0	0	-37.5

Initial Distance (m)	Initial Velocities (mph)	(m/s)	Final Velocities (mph)	(m/s)	Acceleration Change (m/s^2)
40	35	15.6	0	0	-14.8
50	35	15.6	0	0	-9.2
60	35	15.6	0	0	-6.7
70	35	15.6	0	0	-5.3
40	45	20.1	0	0	-41.2
50	45	20.1	0	0	-20.4
60	45	20.1	0	0	-13.6
70	45	20.1	0	0	-10.2
80	45	20.1	0	0	-8.1
60	55	24.6	0	0	-26.1
70	55	24.6	0	0	-18.3
80	55	24.6	0	0	-14.0
90	55	24.6	0	0	-11.4
100	55	24.6	0	0	-9.6
70	65	29.1	0	0	-32.0
90	65	29.1	0	0	-18.2
110	65	29.1	0	0	-12.7
130	65	29.1	0	0	-9.8
150	65	29.1	0	0	-7.9
90	80	35.8	0	0	-35.2
110	80	35.8	0	0	-22.7
130	80	35.8	0	0	-16.8
150	80	35.8	0	0	-13.3
170	80	35.8	0	0	-11.0

From these three situations, it is apparent that the ability to brake sooner leads to better outcomes for avoiding a crash. This is depicted in Figure 51. Circles represent the BICADAS data points at different speeds in Figure 51. The X marker indicates the 0.7 second reaction times of a human driver, and the dash mark represents the 1.5 second reaction times of a human driver as depicted in Figure 51. What is apparent from Figure 51 and Tables 26 – 28 is that at faster initial velocities the delayed reaction of the human driver becomes a greater hindrance to the prevention of a crash. Also, the greater the distance between the vehicles the better chance of braking prior to collision. In turn, BICADAS is more capable at preventing front to front collisions than a human driver.

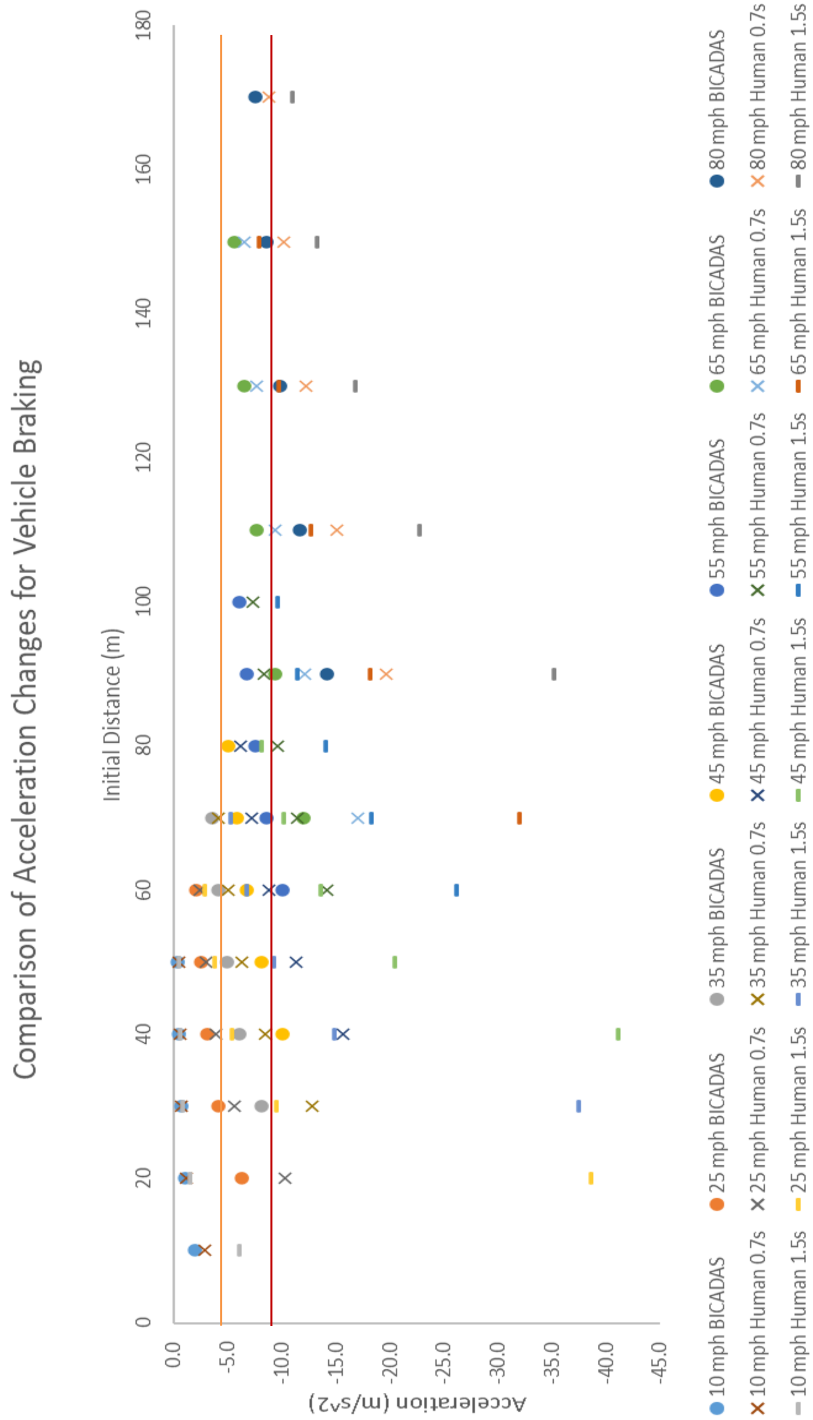

Figure 51. Comparison of the changes in acceleration for BICADAS (circles), 0.7s Human (x), and 1.5s Human (-). Values less than -9.3 (below the red line) indicate a crash, and values less than -4.6 (below the orange line) indicate emergency braking.

The Tables 26 – 28 all represent pure cases of either both vehicles having BICADAS (smart-to-smart) or not having BICADAS (dumb-to-dumb). This leads to the question of a mixed case scenario of one vehicle with BICADAS and the other without BICADAS. For this mixed case BICADAS to non-BICADAS (smart-to-dumb) Table 29 was created. In Table 29, it is assumed that VLC is used for BICADAS so the driver of the non-BICADAS (dumb) vehicle will have a reaction time of 0.7 seconds since they are still visually receiving a warning signal. Both vehicles in Table 29 have a max emergency deceleration of 9.3 m/s^2.

Table 29. Head on impending collision avoidability by emergency braking showing stopping distances for the combined case of BICADAS and non-BICADAS.

Initial Distance	**Initial Velocities**		**Emergency Braking Distance BICADAS**	**Emergency Braking Distance Human (0.7s)**	**Combined Braking Distance**	**Does a Crash Occur**
(m)	**(mph)**	**(m/s)**	**(m)**	**(m)**	**(m)**	**(Crash)**
10	10	4.5	1.1	4.2	5.3	
20	10	4.5	1.1	4.2	5.3	
30	10	4.5	1.1	4.2	5.3	
40	10	4.5	1.1	4.2	5.3	
50	10	4.5	1.1	4.2	5.3	
20	25	11.2	6.7	14.5	21.3	Crash
30	25	11.2	6.7	14.5	21.3	
40	25	11.2	6.7	14.5	21.3	
50	25	11.2	6.7	14.5	21.3	
60	25	11.2	6.7	14.5	21.3	
30	35	15.6	13.2	24.1	37.3	Crash
40	35	15.6	13.2	24.1	37.3	
50	35	15.6	13.2	24.1	37.3	
60	35	15.6	13.2	24.1	37.3	
70	35	15.6	13.2	24.1	37.3	
40	45	20.1	21.8	35.8	57.6	Crash
50	45	20.1	21.8	35.8	57.6	Crash
60	45	20.1	21.8	35.8	57.6	
70	45	20.1	21.8	35.8	57.6	

Initial Distance	Initial Velocities		Emergency Braking Distance BICADAS	Emergency Braking Distance Human (0.7s)	Combined Braking Distance	Does a Crash Occur
(m)	(mph)	(m/s)	(m)	(m)	(m)	(Crash)
80	45	20.1	21.8	35.8	57.6	
60	55	24.6	32.5	49.7	82.2	Crash
70	55	24.6	32.5	49.7	82.2	Crash
80	55	24.6	32.5	49.7	82.2	Crash
90	55	24.6	32.5	49.7	82.2	
100	55	24.6	32.5	49.7	82.2	
70	65	29.1	45.4	65.7	111.1	Crash
90	65	29.1	45.4	65.7	111.1	Crash
110	65	29.1	45.4	65.7	111.1	Crash
130	65	29.1	45.4	65.7	111.1	
150	65	29.1	45.4	65.7	111.1	
90	80	35.8	68.8	93.8	162.6	Crash
110	80	35.8	68.8	93.8	162.6	Crash
130	80	35.8	68.8	93.8	162.6	Crash
150	80	35.8	68.8	93.8	162.6	Crash
170	80	35.8	68.8	93.8	162.6	

What is seen in the combined case BICADAS and non-BICADAS (smart-to-dumb) is that not all crashes could be avoided, but the human driver is the precipitator of the crashes. This can be seen from Table 29 where the emergency braking distance for the human is greater than half the initial distance while the emergency braking distance for BICADAS is less than half the initial distance. Of the fourteen crashes indicated in Table 29, seven were the sole inability of the human driver to brake with enough distance to stop the vehicle. Thus, the inverse is true that BICADAS prevented seven of the fourteen crashes because it was able to begin braking before a human could have reacted.

7.1.2 Front Bumper to Rear Bumper Collision

In the case depicted in Figure 49 (front bumper on rear bumper), the follow vehicle is moving a speed that will intercept with the lead vehicle should neither vehicle alter their velocities nor change lanes. Should the option to change lanes not be available the follow vehicle would need to slowdown. If the deceleration of the follow vehicle is not sufficient to avoid a collision on its own the lead vehicle may need to accelerate to aid in the prevention of the crash. An optimization for this scenario is discussed in section 7.2. Here the physics and dynamics of the problem are analyzed.

Figure 52. Two vehicles facing impending front bumper to rear bumper collision.

Based on Equations 17 and 19 and the scenario depicted in Figure 52, Table 30 was developed. In Table 30, the acceleration needed to match velocities is given as what the follow vehicle would have to accelerate/decelerate (negative indicates deceleration) in order to not crash into the lead vehicle. Accelerations in orange ($\leq$-4.6 m/s^2 & $\geq$-9.3 m/s^2) represent able decelerations that are emergency breaking, and accelerations in red ($\leq$-9.3 m/s^2) represent non-achievable decelerations (crash will occur under present conditions). In the case of the lead vehicle being non-BICADAS (dumb vehicle) with the follower being BICADAS (smart vehicle), only the red conditions would cause a crash should the BICADAS not have a lane to move to available. In the opposite case where the BICADAS (smart vehicle) is the lead and the non-BICADAS (dumb vehicle) is the follow, the BICADAS would recognize the impending crash and accelerate or change lanes to avoid being struck by the other vehicle. In the case of both vehicles being BICADAS (smart-to-smart), the vehicles would perform an optimization as suggested in section 7.2 where the lead vehicle would accelerate and the follow would decelerate if the acceleration needed to match velocities in Table 30 was red or orange. In the smart-to-smart case where the acceleration needed to match velocities is black (≥ -4.6m/s^2) the follow vehicle would just decelerate. This ability to optimize the driving speeds of both vehicles involved will lead to fewer accidents and possibly better traffic flow as it prevents the need for backups caused by emergency braking.

Table 30. Front to Rear bumper impending collision times and accelerations needed to prevent the crash.

Initial Distance	Lead Vehicle Initial Velocity		Follow Vehicle Initial Velocity		Intercept Time	Acceleration Needed to Match Velocities
(m)	(mph)	(m/s)	(mph)	(m/s)	(s)	(m/s^2)
10	45	20.1	40	17.9	No Intercept	No Change Needed
10	45	20.1	45	20.1	No Intercept	No Change Needed
10	45	20.1	50	22.4	4.5	-4.7
10	45	20.1	55	24.6	2.2	-10.0
20	45	20.1	40	17.9	No Intercept	No Change Needed
20	45	20.1	45	20.1	No Intercept	No Change Needed
20	45	20.1	50	22.4	8.9	-2.4
20	45	20.1	55	24.6	4.5	-5.0
30	45	20.1	40	17.9	No Intercept	No Change Needed
30	45	20.1	45	20.1	No Intercept	No Change Needed
30	45	20.1	50	22.4	13.4	-1.6
30	45	20.1	55	24.6	6.7	-3.3
10	55	24.6	50	22.4	No Intercept	No Change Needed
10	55	24.6	55	24.6	No Intercept	No Change Needed
10	55	24.6	60	26.8	4.5	-5.7
10	55	24.6	65	29.1	2.2	-12.0
20	55	24.6	50	22.4	No Intercept	No Change Needed

Initial Distance (m)	Lead Vehicle Initial Velocity (mph)	(m/s)	Follow Vehicle Initial Velocity (mph)	(m/s)	Intercept Time (s)	Acceleration Needed to Match Velocities (m/s^2)
20	55	24.6	55	24.6	No Intercept	No Change Needed
20	55	24.6	60	26.8	8.9	-2.9
20	55	24.6	65	29.1	4.5	-6.0
30	55	24.6	50	22.4	No Intercept	No Change Needed
30	55	24.6	55	24.6	No Intercept	No Change Needed
30	55	24.6	60	26.8	13.4	-1.9
30	55	24.6	65	29.1	6.7	-4.0
10	65	29.1	60	26.8	No Intercept	No Change Needed
10	65	29.1	65	29.1	No Intercept	No Change Needed
10	65	29.1	70	31.3	4.5	-6.7
10	65	29.1	75	33.5	2.2	-14.0
20	65	29.1	60	26.8	No Intercept	No Change Needed
20	65	29.1	65	29.1	No Intercept	No Change Needed
20	65	29.1	70	31.3	8.9	-3.4
20	65	29.1	75	33.5	4.5	-7.0
30	65	29.1	60	26.8	No Intercept	No Change Needed
30	65	29.1	65	29.1	No Intercept	No Change Needed
30	65	29.1	70	31.3	13.4	-2.2
30	65	29.1	75	33.5	6.7	-4.7

7.2 Evaluating the Results of the Biologically Inspired Connected Vehicle Bargaining Optimization

Based on the information discussed in Chapter 6, a Java program was written to perform an Archimedean optimization for vehicle bargaining (communication between the vehicles for the best course of action for both vehicles to take) based on biological inspirations. This code can be found in Appendix C.

7.2.1 Assumptions for BICADAS Optimization Model

A number of assumptions and simplifications were used in the development of the model of the BICADAS bargaining.

- One such assumption is that emergency vehicles would not change from being emergency vehicles.
- Another simplification is that the code is setup only for the case of front bumper to rear bumper type situations as depicted in Figure 52.
- The option to change lanes was not included in the present version of the model as changing lanes represents an added level of complexity.

The values selected for the weights of the Archimedean were set to 0.6, 0.3, and 0.1 for the emergency status, velocities, and accelerations respectively, but other values for the weights could have been chosen. The choice was based on the priority of making sure emergency vehicles received a priority status, and the velocities did not cause the vehicles to crash before worrying what the change in acceleration is practical for the vehicles.

Also, the code differs from the prescribed plan discussed in Chapter 6 to have the vehicles first take the safest action then followed by the optimized action. The present model represents what would occur once communication of a smart-to-smart situation is established. Thus, this model takes place post the initial immediate movement of the safest action. As for finding the best solution an exhaustive search is conducted to find the best new velocities of the two vehicles before comparing them to the nearest and previous solutions for the Archimedean optimization.

Future versions of the model could allow for these vehicles to transition between emergency and non-emergency status depending on whether they are responding to an emergency. Future versions of the model could also allow for the situation of front bumper to front bumper situations as depicted in Figure 50, and the ability to change lanes can be added to future versions of the model.

7.2.2 Analytical Relationships

Finding what the final velocities are for the two vehicles is dependent on the initial velocities and the initial distance between the two vehicles. This follows from Equations 18 and 19. If the follow vehicle's acceleration's change to avoid colliding with the lead vehicle is less than 4.6 m/s^2 in 3 seconds then the follow vehicle will simply slow down. Else the lead vehicles speed will increase as well as decreasing the speed of the follow vehicle. This is iterated through until the minimum change to the velocities of both vehicles is achieved. This also stipulates that using Equation 16 that the max accelerations of both vehicles do not exceed 4.6 m/s^2. The solution is then passed to the Archimedean method to compare the new solution to the previous solution. In the Archimedean weighted sum scheme weights for each of the goals were multiplied to the summation for solving a value, see Equation 24, which was saved to compare to the next solution set during the iteration, see Equation 25.

$$V(\overline{x}_J) = \sum_{i=1}^{3} w_i \overline{x}_{J_i} \tag{24}$$

$$V(\bar{x}_j) \begin{Bmatrix} = \\ > \\ < \end{Bmatrix} V(\overline{x_k}) \tag{25}$$

Should the current value be less than the preceding value the current solution set is saved as the best set and the iteration continues where values of subsequent sets are compared.

7.2.2.1 Program Flowcharts

The program operates several methods that pass and call information from each other. The overall flow of the program is depicted in Figure 53. Figure 54 depicts the inheritance of each of the methods and shows what is passed between the methods.

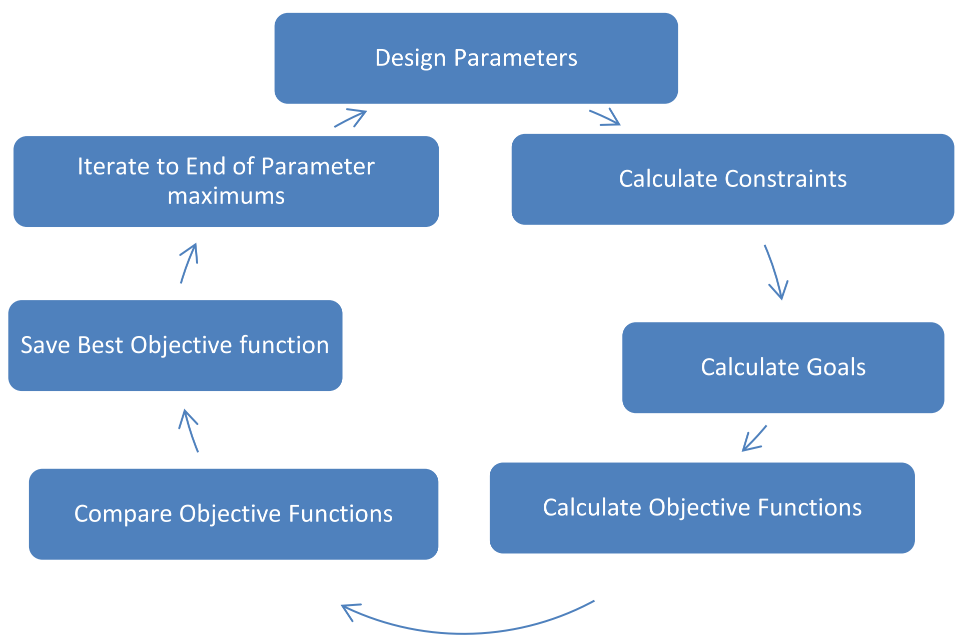

Figure 53. Program flowchart for finding the best solution.

Figure 54 shows how the Java code for the BICADAS bargaining optimization, found in Appendix C, methods interact with each other for what is passed between them.

In the Java code, the Main method calls the Archimedean, AccelerationValue, and Velocity methods. The Main method passes the velocities and the distance to the Velocity method while it receives back an array of new velocities. The main method then passes velocity values to the AccelerationValue method and is returned the numerical acceleration value for the velocities given. Finally, the Main method calls the Archimedean method and sends it weights and solution sets of emergency statuses, velocities, and accelerations to compare to determine if the new solution is better than the previous best solution.

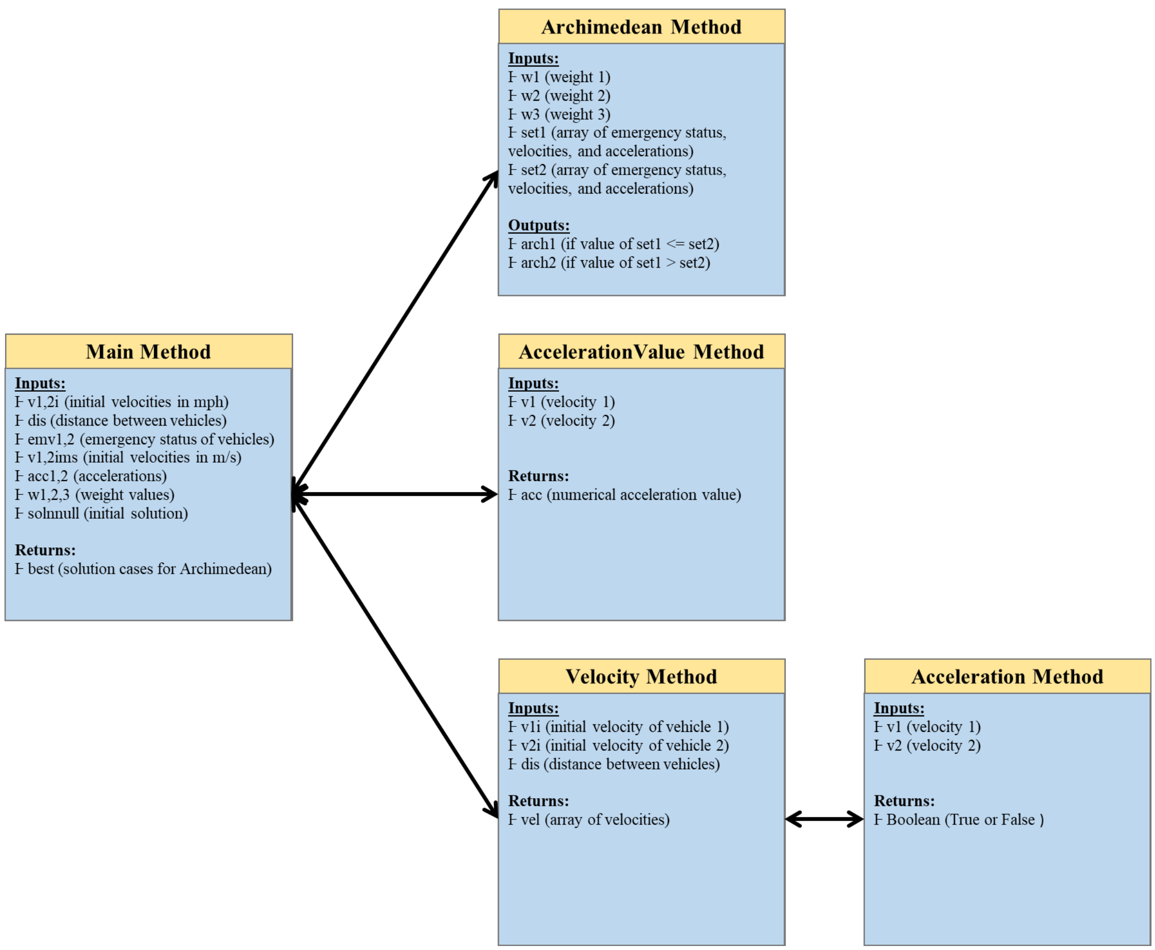

Figure 54. Flow chart of the Java methods and what they pass between them.

7.2.3 *Results and Verification*

Running the BICADAS bargaining optimization code found in Appendix C, the results for a scenario where both vehicles are of the same emergency level was run for the lead vehicle having varying initial velocities between 35 mph (15.6 m/s) and 65 mph (29.1 m/s) and varying initial distances ranging from 10 meters to 40 meters between the two vehicles. The follow vehicle's velocity was held constant at 80 mph (35.8 m/s). Both vehicles are assumed to have BICADAS and are able to communicate with each other. From this scenario Table 31 is derived.

Table 31. Optimization of Velocities for the 2 BICADAS vehicles for front to rear bumper collision.

Initial Distance	Lead Vehicle Initial Velocity		Follow Vehicle Initial Velocity		Lead Vehicle Final Velocity		Acceleration of Lead Vehicle	Follow Vehicle Final Velocity		Acceleration of Follow Vehicle
(m)	(mph)	(m/s)	(mph)	(m/s)	(mph)	(m/s)	(m/s^2)	(mph)	(m/s)	(m/s^2)
10	35	15.6	80	35.8	55	24.6	4.5	60	26.7	4.5
20	35	15.6	80	35.8	51	22.7	3.5	64	28.7	3.5
30	35	15.6	80	35.8	48	21.6	3	67	29.8	3.0
40	35	15.6	80	35.8	44	19.6	2	71	31.8	2.0
10	45	20.1	80	35.8	61	27.1	3.5	64	28.7	3.5
20	45	20.1	80	35.8	56	25.1	2.5	69	30.8	2.5
30	45	20.1	80	35.8	52	23.1	1.5	73	32.8	1.5
40	45	20.1	80	35.8	49	22.1	1	76	33.8	1.0
10	55	24.6	80	35.8	64	28.6	2	71	31.7	2.0
20	55	24.6	80	35.8	62	27.6	1.5	73	32.8	1.5
30	55	24.6	80	35.8	57	25.6	0.5	78	34.8	0.5
40	55	24.6	80	35.8	55	24.6	0	80	35.8	0.0
10	65	29.1	80	35.8	65	29.1	0	71	31.7	2.0
20	65	29.1	80	35.8	65	29.1	0	78	34.8	0.5
30	65	29.1	80	35.8	65	29.1	0	80	35.8	0.0

Initial Distance	Lead Vehicle Initial Velocity		Follow Vehicle Initial Velocity		Lead Vehicle Final Velocity		Acceleration of Lead Vehicle	Follow Vehicle Final Velocity		Acceleration of Follow Vehicle
(m)	(mph)	(m/s)	(mph)	(m/s)	(mph)	(m/s)	(m/s^2)	(mph)	(m/s)	(m/s^2)
40	65	29.1	80	35.8	65	29.1	0	80	35.8	0

One interesting thing that is observable from Table 31 (highlighted in yellow) is sometimes neither vehicle changes their respective velocity. This is because for the initial set distance the time needed for the two vehicles' paths to intersect is greater than 3 seconds. Recall that 3 seconds is the minimum time needed for a human driver to keep proper spacing to prevent a crash. To validate this Table 30's initial values were run through the BICADAS bargaining optimization program as shown in Table 32.

Table 32. Optimization of Velocities for the 2 BICADAS vehicles using initial values from Table 30.

Initial Distance	Lead Vehicle Initial Velocity		Follow vehicle Initial Velocity		Lead Vehicle Final Velocity		Acceleration of Lead Vehicle	Follow Vehicle Final Velocity		Acceleration of Follow Vehicle
(m)	(mph)	(m/s)	(mph)	(m/s)	(mph)	(m/s)	(m/s^2)	(mph)	(m/s)	(m/s^2)
10	45	20.1	40	17.9	45	20.1	0.0	40	17.9	0.0
10	45	20.1	45	20.1	45	20.1	0.0	45	20.1	0.0
10	45	20.1	50	22.4	45	20.1	0.0	50	22.4	0.0
10	45	20.1	55	24.6	45	20.1	0.0	51	22.6	1.0
20	45	20.1	40	17.9	45	20.1	0.0	40	17.9	0.0
20	45	20.1	45	20.1	45	20.1	0.0	45	20.1	0.0
20	45	20.1	50	22.4	45	20.1	0.0	50	22.4	0.0
20	45	20.1	55	24.6	45	20.1	0.0	55	24.6	0.0
30	45	20.1	40	17.9	45	20.1	0.0	40	17.9	0.0
30	45	20.1	45	20.1	45	20.1	0.0	45	20.1	0.0
30	45	20.1	50	22.4	45	20.1	0.0	50	22.4	0.0

Initial Distance	Lead Vehicle Initial Velocity		Follow vehicle Initial Velocity		Lead Vehicle Final Velocity		Acceleration of Lead Vehicle	Follow Vehicle Final Velocity		Acceleration of Follow Vehicle
(m)	(mph)	(m/s)	(mph)	(m/s)	(mph)	(m/s)	(m/s^2)	(mph)	(m/s)	(m/s^2)
30	45	20.1	55	24.6	45	20.1	0.0	55	24.6	0.0
10	55	24.6	50	22.4	55	24.6	0.0	50	22.4	0.0
10	55	24.6	55	24.6	55	24.6	0.0	55	24.6	0.0
10	55	24.6	60	26.8	55	24.6	0.0	60	26.8	0.0
10	55	24.6	65	29.1	55	24.6	0.0	61	27.0	1.0
20	55	24.6	50	22.4	55	24.6	0.0	50	22.4	0.0
20	55	24.6	55	24.6	55	24.6	0.0	55	24.6	0.0
20	55	24.6	60	26.8	55	24.6	0.0	60	26.8	0.0
20	55	24.6	65	29.1	55	24.6	0.0	65	29.1	0.0
30	55	24.6	50	22.4	55	24.6	0.0	50	22.4	0.0
30	55	24.6	55	24.6	55	24.6	0.0	55	24.6	0.0
30	55	24.6	60	26.8	55	24.6	0.0	60	26.8	0.0
30	55	24.6	65	29.1	55	24.6	0.0	65	29.1	0.0
10	65	29.1	60	26.8	65	29.1	0.0	60	26.8	0.0
10	65	29.1	65	29.1	65	29.1	0.0	65	29.1	0.0
10	65	29.1	70	31.3	65	29.1	0.0	70	31.3	0.0
10	65	29.1	75	33.5	65	29.1	0.0	71	31.5	1.0
20	65	29.1	60	26.8	65	29.1	0.0	60	26.8	0.0
20	65	29.1	65	29.1	65	29.1	0.0	65	29.1	0.0
20	65	29.1	70	31.3	65	29.1	0.0	70	31.3	0.0
20	65	29.1	75	33.5	65	29.1	0.0	75	33.5	0.0
30	65	29.1	60	26.8	65	29.1	0.0	60	26.8	0.0
30	65	29.1	65	29.1	65	29.1	0.0	65	29.1	0.0
30	65	29.1	70	31.3	65	29.1	0.0	70	31.3	0.0
30	65	29.1	75	33.5	65	29.1	0.0	75	33.5	0.0

In comparing Table 32 to Table 30, it becomes apparent that only in the cases where the time for the vehicles to intercept each other (crash), less than 3 seconds causes the optimization program take control, highlighted in yellow. This stems from the minimum safe follow distance being 3 seconds for a human to react to avoid a crash. Hence, once the

3 seconds of spacing is violated the program comes into effect to guide the vehicles to avoid the crash.

For validating the solution method, the scenario of no emergency vehicles with the lead vehicle going 45 mph (20.1 m/s) and the follow vehicle going 80 mph (35.8 m/s) with an initial spacing of 10 meters was selected. The initial velocities were plotted along with each step to the final solution, and then one step beyond the found solution was plotted as shown in Figure 55. The Archimedean values for each step were labelled on the scatter plot of solutions. It is important to note when viewing Figure 55 that the step just prior to the solution still has the vehicles crashing, and it is therefore not a valid solution point. Notice the point labelled “Final Solution” has an Archimedean value less than the point labelled “One Step Beyond Solution”; therefore, the point labelled “Final Solution” is the best solution for the vehicle velocities as this Archimedean optimization is setup. Thus, the optimal solution is for the lead vehicle to increase its velocity to 61 mph and for the follow vehicle to decrease its velocity to 64 mph in order to prevent a crash so long as neither vehicle can change lanes.

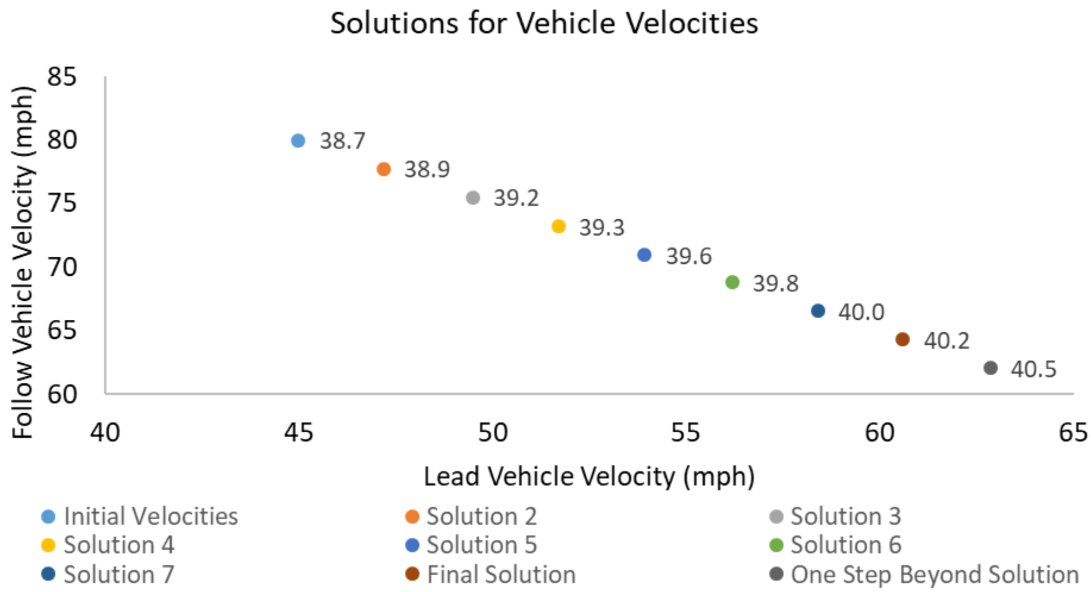

Figure 55. Solutions for vehicle velocities for the initial velocities of 45mph and 80 mph.

The same scenario as used in Figure 55, front bumper to rear bumper with lead vehicle initial velocity of 45 mph and follow vehicle velocity of 80 mph, with varying Archimedean weights. The weights for the emergency vehicle status, velocity, and acceleration were varied from 0 to 1 for calculating the Archimedean values to determine the Pareto frontier as shown in Figure 56. Finding the Pareto frontier as shown in Figure 56 allows for seeing if any trade-offs among the weights for the Archimedean would benefit in finding other feasible solutions. As the plot of Figure 56 shows that there is a flat surface, so there is no benefit from varying the weights to the Archimedean as structured in the Java code.

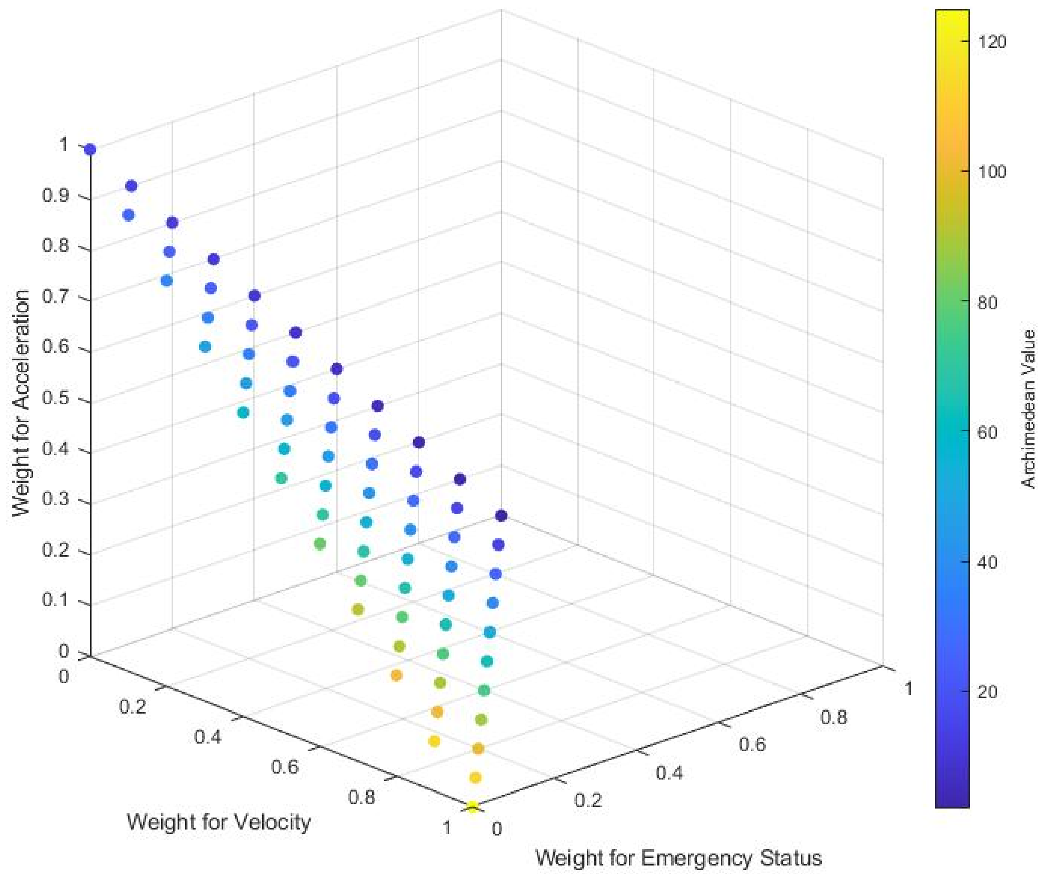

Figure 56. Pareto frontier for varying weights to the Archimedean optimization for initial velocities of 45mph and 80 mph.

7.3 Summary

The crucial aspect of this research is to see if biological principles can be applied to vehicle ADAS to reduce the occurrence of crashes. As shown in repeatably in Tables 26 – 30 and in the Java optimization, by applying biological principles to ADAS in the proposed form of BICADAS crashes are able to be prevented with great success over even the best human driver reactions. This holds true for the two main fatal crash occurrence types of front bumper to front bumper and front bumper to rear bumper. This leads to the discussion in Chapter 8 about whether BICADAS should succeed ADAS.

CHAPTER 8. COMPARISON OF THE COMPETING PATHS FOR FUTUTRE ADAS DEVELOPMENT

8.1 Comparison of BICADAS to ADAS

Comparing the present state of ADAS technology with the proposed BICADAS is no simple task. Present ADAS is affected by many factors and not all are easily quantifiable. For example dealing with the human factor involved with present ADAS is hard to quantify as discussed in Chapter 4. Looking at past driving history and demographics are some ways to quantify the human factor, but the in-the-moment actions are much more difficult to quantify. For the sake of comparison, the human factor has been simplified to be the standard reaction time of 0.7 seconds to 1.5 seconds. The lower reaction time of 0.7 seconds is utilized for the cases where ADAS simply provides a warning to the driver.

BICADAS on the other hand removes the human factor after the 3 second time spacing for intervention is reached. This is shown in Tables 26 – 30 and Figure 51 in Chapter 7. For example, take Table 26 and Table 27 and combine them as done in Table 33. It is observable that for these cases of front bumper on front bumper crashes, the BICADAS prevents 7 of the 14 crashes (shown in red) occurring for the human driver. The reason the 0.7 second reaction time is used instead of the 1.5 seconds reaction time is due to the idea that the vehicle has ADAS that is providing a warning to the driver.

Table 33. Combination of Tables 26 and 27 for comparing the accelerations of BICADAS and humans. Orange highlights are emergency braking, and red highlights are crashes.

Initial Distance (m)	Initial Velocities (mph)	(m/s)	BICADAS Acceleration Change (m/s^2)	0.7 Human Acceleration Change (m/s^2)
10	10	4.5	-2.0	-2.9
20	10	4.5	-1.0	-1.2
30	10	4.5	-0.7	-0.7
40	10	4.5	-0.5	-0.5
50	10	4.5	-0.4	-0.4
20	25	11.2	-6.2	-10.3
30	25	11.2	-4.2	-5.6
40	25	11.2	-3.1	-3.9
50	25	11.2	-2.5	-3.0
60	25	11.2	-2.1	-2.4
30	35	15.6	-8.2	-12.9
40	35	15.6	-6.1	-8.4
50	35	15.6	-4.9	-6.3
60	35	15.6	-4.1	-5.0
70	35	15.6	-3.5	-4.1
40	45	20.1	-10.1	-15.6
50	45	20.1	-8.1	-11.3
60	45	20.1	-6.7	-8.8
70	45	20.1	-5.8	-7.2
80	45	20.1	-5.1	-6.1
60	55	24.6	-10.1	-14.1
70	55	24.6	-8.6	-11.5
80	55	24.6	-7.6	-9.6
90	55	24.6	-6.7	-8.3
100	55	24.6	-6.0	-7.3
70	65	29.1	-12.1	-17.0
90	65	29.1	-9.4	-12.1
110	65	29.1	-7.7	-9.4
130	65	29.1	-6.5	-7.7
150	65	29.1	-5.6	-6.5
90	80	35.8	-14.2	-19.7
110	80	35.8	-11.6	-15.1
130	80	35.8	-9.8	-12.2

Initial Distance	Initial Velocities		BICADAS Acceleration Change	0.7 Human Acceleration Change
(m)	(mph)	(m/s)	(m/s²)	(m/s²)
150	80	35.8	-8.5	-10.2
170	80	35.8	-7.5	-8.8

The same can be seen in the front bumper to rear bumper case as shown by Table 34. In Table 34, the BICADAS of two vehicles working together is able to prevent all 3 of the crashes (shown in red) the human driver with ADAS alone would have experienced. BICADAS was also able to reduce the need for emergency braking (shown in orange).

Table 34. Comparing accelerations of two vehicles with BICADAS versus present ADAS. Orange highlights are emergency braking, and red highlights are crashes.

Initial Distance (m)	Lead Vehicle Initial Velocity (mph)	Lead Vehicle Initial Velocity (m/s)	Follow vehicle Initial Velocity (m/s²)	Follow vehicle Initial Velocity (m/s)	2 BICADAS Acceleration (m/s²)	ADAS Acceleration (m/s²)
10	45	20.1	40	17.9	No Change Needed	No Change Needed
10	45	20.1	45	20.1	No Change Needed	No Change Needed
10	45	20.1	50	22.4	-2.9	-4.7
10	45	20.1	55	24.6	-5.0	-10.0
20	45	20.1	40	17.9	No Change Needed	No Change Needed
20	45	20.1	45	20.1	No Change Needed	No Change Needed
20	45	20.1	50	22.4	-1.7	-2.4
20	45	20.1	55	24.6	-2.5	-5.0
30	45	20.1	40	17.9	No Change Needed	No Change Needed
30	45	20.1	45	20.1	No Change Needed	No Change Needed
30	45	20.1	50	22.4	-0.8	-1.6
30	45	20.1	55	24.6	-1.7	-3.3
10	55	24.6	50	22.4	No Change Needed	No Change Needed
10	55	24.6	55	24.6	No Change Needed	No Change Needed
10	55	24.6	60	26.8	-2.9	-5.7

Initial Distance (m)	Lead Vehicle Initial Velocity (mph)	(m/s)	Follow vehicle Initial Velocity (m/s^2)	(m/s)	2 BICADAS Acceleration (m/s^2)	ADAS Acceleration (m/s^2)
10	55	24.6	65	29.1	-6.0	-12.0
20	55	24.6	50	22.4	No Change Needed	No Change Needed
20	55	24.6	55	24.6	No Change Needed	No Change Needed
20	55	24.6	60	26.8	-1.5	-2.9
20	55	24.6	65	29.1	-3.0	-6.0
30	55	24.6	50	22.4	No Change Needed	No Change Needed
30	55	24.6	55	24.6	No Change Needed	No Change Needed
30	55	24.6	60	26.8	-1.0	-1.9
30	55	24.6	65	29.1	-2.0	-4.0
10	65	29.1	60	26.8	No Change Needed	No Change Needed
10	65	29.1	65	29.1	No Change Needed	No Change Needed
10	65	29.1	70	31.3	-3.4	-6.7
10	65	29.1	75	33.5	-7.0	-14.0
20	65	29.1	60	26.8	No Change Needed	No Change Needed
20	65	29.1	65	29.1	No Change Needed	No Change Needed
20	65	29.1	70	31.3	-1.7	-3.4
20	65	29.1	75	33.5	-3.5	-7.0
30	65	29.1	60	26.8	No Change Needed	No Change Needed
30	65	29.1	65	29.1	No Change Needed	No Change Needed
30	65	29.1	70	31.3	-1.1	-2.2
30	65	29.1	75	33.5	-2.4	-4.7

As for how the use of 0.7 seconds applies to comparing BICADAS to current ADAS, only a warning to the human driver is given at the lowest level of intervention from current ADAS and at the highest level the ADAS takes control of the vehicle. In neither case is the vehicle communicating with other vehicles. In cases where BICADAS is only present in one of the two vehicles, the BICADAS would function similar to the highest levels of current ADAS. In cases where both vehicle have BICADAS, the added bonus of communication between the vehicle leads to more advantageous outcomes. Having vehicles connected as is the case with BICADAS may lead to other benefits, which will be discussed in section 8.3.

8.2 Investment of ADAS and BICADAS

As discussed previously in Chapters 1 and 4, there have been significant investments made into the development of ADAS and supporting infrastructure. More than $29.9 billion has been invested by companies into ADAS technology research with averages each year ranging from $0.6 billion in 2010 to $5.6 billion in 2019 (Daniel Holland-Letz 2019). The total investment is expected to increase to over $91.8 billion by 2025 (Markets 2020). As BICADAS is a continuation of ADAS development it would be included in that growth to $91.8 billion.

8.2.1 Technology Upgrades

ADAS technologies in vehicles differ from one manufacturer to the next and the technology offerings will differ even among a vehicle model because of the vehicle's trim level (Automotive 2019). The differences can be as much as a few thousand dollars between a vehicle with the bare minimum ADAS required by law to a vehicle with all the latest ADAS technologies available. Because of the varying outfitting of vehicles with respect to ADAS, different cost for BICADAS upgrades to existing vehicles would exist. Vehicles that already have ADAS with many of the most recent technologies such as adaptive cruise control with stop and go technology would likely only require a software upgrade to have BICADAS, assuming visual light communication (VLC) is used for connectivity. If one of the other connectivity protocols is used other costs such as hardware installation would be needed as well. Other vehicles with older ADAS technologies would likely require the addition of wiring, possibly sensors, and computer chips in addition to the software to upgrade them to BICADAS. This in turn would cost a few hundred dollars to install these upgrades to the older ADAS equipped vehicles as shown in Table 35. The cost for the software upgrade in Table 35 was based on the software upgrade for Ford's navigation system and wiring (Ford 2020). The costs for the other hardware listed in Table 35 (control boards, cameras, and adaptive cruise control with stop and go) and wiring was determined based on searches from Amazon.com.

Table 35. Technology level upgrade cost to BICADAS from present technology level.

Technology Level	***Upgrade to BICADAS***	***Cost ($)***
BICADAS	None	0
High-end ADAS	Software, Some Wiring	160
Low-end ADAS	Software, Extensive Wiring, Control Boards, Camera Array, Adaptive Cruise Control w/ Stop & Go	490
No ADAS	Software, Extensive Wiring, Control Boards, Camera Array, Adaptive Cruise Control w/ Stop & Go	490

8.2.2 Sensor Repair Costs

While repairs play a lesser role in the cost outcome for accidents than injury cost, they do still contribute to the overall costs as discussed in Chapter 5. When these systems are affected by a crash they at a bare minimum need to be recalibrated. Recalibration alone can cost $250-$300 USD as shown in Table 22, which is reproduced below in Table 36. By BICADAS reducing the occurrence of even more crashes than present ADAS the consumer will save on the cost of repairs. By preventing the front bumper crashes, BICADAS could save as much as $4300, and in rear bumper crashes could save as much as $4550 by having BICADAS as shown in Table 36.

Table 36. Cost (USD) of repairing vehicle components (Association 2018, Preston 2020).

Part	Min	Max
Front Bumper	1450	4300
Headlights and Taillights	300	1750
Windshield	1750	3650
Rear Bumper	1950	4550
Side Mirror	1250	2750

8.3 Other Potential Benefits from BICADAS

Other potential benefits from BICADAS include faster commute times, better fuel economy, less traffic congestion, and less need for new vehicles to replace those in accidents, as will be discussed below. A number of these benefits are similar to the sustainability benefits of ADAS discussed in Chapter 5.

8.3.1 Environmental Impact

By reducing the number of crashes with significant damage the amount of CO_2 is produced as a byproduct of the manufacturing along with reductions in other material usage such as copper, zinc, steel, aluminum, and plastics. As shown in Figure 34, reproduced above as Figure 57, the amount of CO_2 and H_2O saved on a per vehicle basis, assumes average vehicle weighing EPA class 2 minimum of 6,001lbs (2722kg), is rather significant (Argonne National Laboratory 2020). Should BICADAS reduce fatal crashes by the idealized 94% (approximately 47,000 vehicles) that would lead to a reduction in 138 million kg of CO_2 and 514,000 m^3 of water saved annually. A 30% (15,000 vehicles) reduction in fatal crashes due to BICADAS would save 44 million kg of CO_2 and 164,000 m^3 of water. To provide perspective those are 205.6 and 65.6 Olympic size swimming pools of water respectively. Based on the findings of (Fish and Bras 2021) there appears to be a real-world reduction of fatal crashes for vehicles with effective ADAS between 70% and 93%, and the adoption of BICADAS could potentially push even the less effective ADAS equpped vehicles up to the same percentage reductions in crashes.

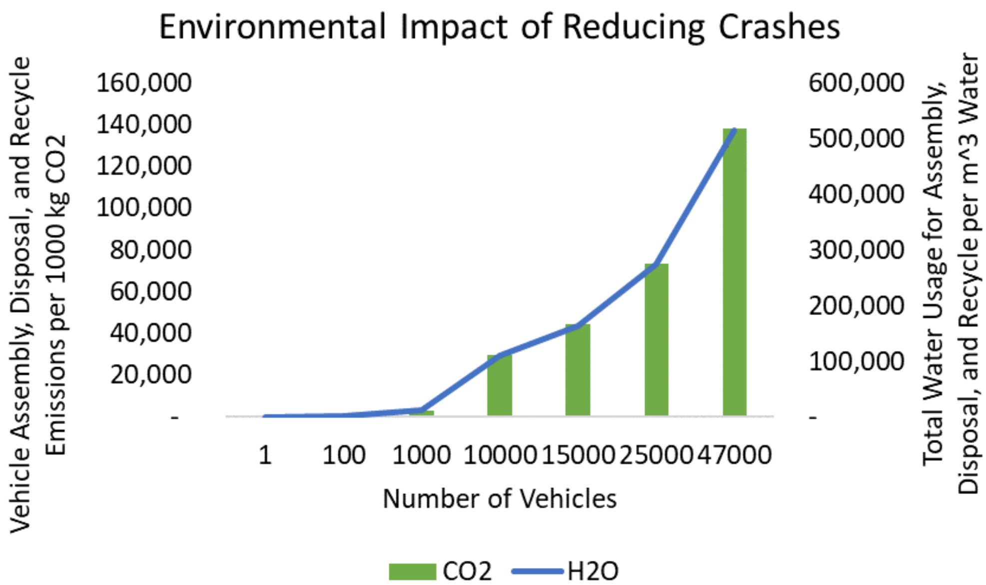

Figure 57. CO_2 and H_2O savings of preventing crashes of pickup trucks.

8.3.2 Fuel Economy

One of the advantages that comes from traffic not needing to slow down due to other drivers choosing to drive at a leisurely speed is the lower congestion on the roads. By not having to slow down like their ADAS counter parts the BICADAS equipped vehicles (in a smart to smart scenario) avoid the energy expenditure that stems from the changes in speed. For example when you are driving your vehicle on the freeway and using cruise control to maintain a constant speed you will get better fuel economy than if you were to be constantly speeding up and slowing down to keep pace with traffic. Because BICADAS (in a smart to smart scenario) mitigates the compression of traffic spacing, the vehicles are able to keep moving at reasonable speeds which provides faster commute times and better fuel economy.

8.4 Summary

There exist advantages of BICADAS over present ADAS. BICADAS being able to intercede in situations similar to who adaptive cruise control with stop and go technology works on the freeway, but BICADAS is able to do this function for all driving situations. This is just one of the advantages BICADAS has over ADAS. Along with potentially improved travel times and less frustration due to traffic congestions for drivers for the smart to smart interaction scenario, BICADAS can contribute to environmental sustainability at a level at least as good as the impacts of ADAS as discussed in section 3. Based on the cases tested in Table 34, BICADAS for two vehicles was able to prevent all 36 crashes compared to ADAS preventing only 33 crashes. This is in addition to only needing to emergency brake 3 times for BICADAS compared to 10 times for ADAS, to include the 3 crashes. While ADAS, found to be effective for FSLDPTs, was able to reduce fatal crashes between 70% and 94%, BICADAS could potentially push all equipped vehicles to the idealized 94% reduction in crashes for both fatal and non-fatal. These positive outcomes are produced with technology with a relatively low cost required to upgrade existing ADAS vehicles to be BICADAS enabled. It is thus natural that BICADAS should be the subsequent phase in the advancement of ADAS technology.

CHAPTER 9. SUMMARY AND FUTURE WORK

9.1 Summary of Work

The research question (RQ) and goals (RGs) were answered through the completion the following research tasks (RT). It is important to recall that the data utilized in this work comes from the NHTSA FARS database, which is based solely on fatal accident data.

9.1.1 Research Tasks (RT) Completed

RT1. Real-world accident data was collected thorough literature reviews, data mining, financial reports, and internet searches. See Chapter 2 sections 1, 5, and 6 and Chapter 4 section 1.

RT2. Collected information on biological principles for comparison, with thorough literature reviews and internet searches. See Chapter 2 sections 2 and 3 and Chapter 6.

RT3. Analyzed the datasets of real-world data using heuristics and stochastic analysis with a focus on FSLDPTs. See Chapter 4.

- **a.** Compared the heuristics for the FSLDPTs among all seven automobile manufacturers. See Chapter 4 sections 2 and 3.
- **b.** Broke out the FSLDPTs with ADAS from the rest of the FSLDPTs.
    - i. Identified a common grouping for FSLDPTs with ADAS for a relative comparison among the brands. See Chapter 2 section 6 and Chapter 4 section 1.

ii. Identified factors used to assess the performance of ADAS. See Chapter 4 section 1.

c. Performed stochastic analysis to determine statistical significance of FSLDPT with ADAS performance. See Chapter 4 sections 2 and 3.

d. Performed stochastic analysis to determine contributing factors statistical significance of FSLDPT with ADAS performance. See Chapter 4 sections 2 and 3.

RT4. Analyzed the economic metrics associated with cost of an accident.

a. Optimized impact location selection using repair cost, injury cost, and injury severity to determine the best and the worst vehicle locations to be impacted. See Chapter 5.

RT5. Investigated whether it is better for automobile manufacturers to continue the present trajectory of ADAS development or explore V2V based on biological inspiration. See Chapter 8.

a. Used existing accident data to develop a model for future accidents based on current trends in accident/injury reduction. See Chapter 5 and Chapter 8.

b. Using biological inspired principles as a benchmark, a model was developed for vehicles using present ADAS accident data in a V2V setup (BICADAS). See Chapters 6, 7 and 8.

9.1.2 Detailed Work Completed

RT1: A detailed and exhaustive set of accident automotive data was a vital component for this research. There existed multiple avenues for ascertaining this data following a thorough literature reviews, data mining, financial reporting, and internet searches. Literature included (but were not limited to) consumer reports, government reports, traffic journals, accident journals, consulting firm reports, insurance reports, and technical journals. Data mining was available through insurance agencies, NHTSA, IIHS, state government accident reports. Financial reporting was obtained through SEC annual reports such as company 10-K and 20-F reports. Internet searches included (but not limited to) sales brochures and traffic safety factsheets. As for obtaining real-world complete and detailed accident data there exists no such data set. Partial sets are available through insurance agencies; however, these are proprietary data sets and due to privacy laws were next to impossible to obtain. Each state produces limited detailed fatal accident reports that are inconsistent from state to state making unification of these independent incongruent datasets unrealistic. By limiting the real-world data to a complete and detailed set of accidents resulting in one or more fatalities, a useful and detailed data set was obtained from NHTSA known as FARS. NHTSA also produces a speculative dataset that generalizes non-fatal accidents known as the Crash Report Sampling System (CRSS). The NHTSA FARS data was organized, sorted, queried, and analyzed in RT3.

RT2: Self organized movement in aggregations of organisms (i.e. swarms, flocks, schools) is a common occurrence in nature. A thorough literature review of academic journals was conducted. The patterns and trends from literature were combined with the data analyzed from RT3 to construct the BICADAS model for RT5's biologically inspired V2V (vehicle-to-vehicle) self-organization. While there are V2V models that have been developed, none of those models have looked at incorporating biologically inspired principles. Some existing research for V2X (vehicle-to-infrastructure/vehicle) points out the limitations of data transfer between sender and receiver (Nadeem, Dashtinezhad et al. 2004). Other research in V2X deals with how the vehicles interact to avoid accidents based on how the research perceives a system should work (Yang, Liu et al. 2004, Kunze, Haberstroh et al. 2011, Hafner, Cunningham et al. 2013, Yuan, Tasik et al. 2020). This work used biological inspiration for the methodology of how V2V should interact, which has not been applied previously by other researchers.

RT3: The data assembled (NHTSA FARS) and organized as part of RT1 was filtered for the seven FSLDPTs. The data was then graphed to visualize the factors in the dataset. From the factors identify those that can be used to compare the accidents were Level of Injury and Damage Severity. Comparing the two factors identified for comparing accidents to select one factor (Level of Injury) was used for all comparisons. The seven brands of FSLDPTs are normalized by dividing the total accidents by the number of units sold in the corresponding year found using financial reports and internet searches. Then FSLDPT brands were compared after normalization using the factors from the dataset. The FSLDPTs equipped with ADAS were then be broken out using identifying factors (trim level, vehicle model year, cabin size, and engine size) from the dataset. These factors were identified through the use of sales brochures. With the ADAS equipped FSLDPTs identified, statistical analysis such as ANOVA tests were performed to identify factors that influence the performance of ADAS FSLDPTs.

RT4: The only way automotive manufacturers will change how they are deploying ADAS technology is if market forces shift their interests. Economics of accidents is one of such market forces that can have that effect. Economic and accident data obtained in RT1 was used to create a model that was optimized to indicate where the most expensive and severe impacts occur for an accident. It was used to determine future deployment needs and designs of ADAS technologies. It also helped distinguish between ADAS for safety and ADAS for convenience. By using a single dataset for pricing of components (Automotive 2019), even if the quoted values for the components was inaccurate the relativism of the pricing used in the model was consistent. The results from the optimization support RT5a for reasoning on what needs continued improvement and investment and RT5b for what issue doe the biological inspiration need to address most predominately.

RT5: The two directions (current ADAS and BICADAS) that could be taken for the next stage of ADAS development was investigated. RT5a was to perform a regression analysis based on the trends in investment, pricing, accident occurrence, and injury severity. RT5b involved developing a model for CV using principles inspired from biology. The patterns from ants, birds, cockroaches, dolphins, and fish were strong influences on the model. Their principles were used to examine how to pass information between the CVs and for recognizing which vehicles should communicate. These two tasks' resultant models were then be compared for accident occurrence, and associated costs.

9.2 Contributions

This dissertation advances the work being done in ADAS technology development through modeling and simulation grounded in quantified real-world data. Even though limited real-world data has been used to in models and simulations of motor vehicle accidents, the incorporation of biologically inspired self-organization for cohort movement has not been proposed or evaluated for efficacy of mitigating automotive accidents and injuries.

The outcomes of this research are:

(i) The validation of the central hypothesis that connected vehicles inspired by biological principles can produce better outcomes for collision avoidance than non-connected vehicles.

(ii) A biologically inspired connected vehicle model validated through simulations that combines the human engineered system and biological solutions. The biologically inspired model (BICADAS) provides guidance for the connection of vehicles which is suitable for the industrial sector to develop derivatives for V2V networks.

(iii) The first study of the effectiveness of ADAS in FSLDPTs. This work provides insight to a large percentage (18%) of registered vehicles on the roads in the United States that has been neglected in past studies of ADAS because of its exclusivity of being neither a sedan nor a freight truck.

(iv) Identifying which ADAS technologies were effective at reducing accidents and reducing the severity of injuries contrasted to those which exist for driver convenience was presented as conferences. This translates to auto-manufacturers being able to stratify which technologies are worth continued improvement, which are satisfactory as is, or which could be depreciated while still providing the same level of aptitude. This contribution has informed the research community where to focus their efforts to provide the largest return on investment.

(v) Provides an insight into the economics of ADAS regarding costing and pricing. By evaluating the cost to the consumer for the level of additional safety provided by

ADAS technologies offered by a particular auto-manufacturer relative to other auto-manufacturers, the consumer will be better equipped to make a conscientious decision when purchasing a vehicle. Auto-manufacturers have gained knowledge of how much to invest to see improvement in vehicle safety.

9.3 Future Work

This dissertation has laid the foundation for the future development of ADAS and vehicle autonomy. Reaction times for BICADAS physics estimations should include for sensor processing and computation time. A cursory check was done to the physics calculations in this work and found that should computation time for BICADAS take 0.1 second, an over estimate of time for cameras to process data and for data to be transferred between vehicles, there would be no change in occurrences of emergency braking or crashes as were previously computed. In the case of visual sensors such as cameras, the rate of frames per second should be included in the reaction time of BICADAS. This work did include a factor of safety of 1.5 for BICADAS Java code, but future work could fine tune that to be more precise to the available technology rather than giving a blanket 1 second of travel distance buffer for the reaction of BICADAS. The next stage following this work would be to expand the Java bargaining code to be able to address more scenarios. Then physical test of the BICADAS technology can be done to prove out their effectiveness.

9.3.1 Expand the Java Bargaining Code to include

The Java code presented in chapters 6 and 7 is rudimentary. It was designed to address one subset of the smart-smart scenario (front to rear). This particular scenario was targeted in the Java code due to its overwhelming occurrence in real-world crashes. More work on the bargaining code needs to be done to include other scenarios such as the addition front to front case in the smart-smart scenario as well as the inclusion of the other communication scenarios (smart-semi smart, smart-dumb).

Other features should also be included in the updates to the Java code. The ability to have emergency vehicles change to non-emergency status will be useful for maintaining a smooth traffic flow. More importantly having the code recognize that changing lanes can be optimal in certain cases would likely lead to BICADAS avoiding more crashes and reduce the need to emergency brake even further. By recognizing that vehicles have varying EPA class weights in the Java code, accelerations can be tailored to the specific vehicles involved. This would improve the precision of targeting velocity changes of each vehicle involved.

A higher-level systems analysis should be conducted to see how BICADAS performs when multiple vehicle interactions occur. This would validate BICADAS as being able to improve travel flow and prevent traffic congestion. It would also likely show tertiary benefits of faster travel times and better efficiencies of fuel consumption.

9.3.2 Physical Testing of BICADAS

Once the bargaining code has been updated, building physical testing apparats for BICADAS can be done. A vision system to identify different VLC signals for BICADAS would need to be designed and programmed to feed information into the bargaining code. Once that was established, small-scale testing of BICADAS could be initially done using remote-control vehicles in a lab setting. This would in turn would potentially lead to advances in swarm robotics as the automotive problem is more complex than what is currently being done in swarm robotics due the greater complexity of the problem that was discussed in Chapter 2 section 4. Then BICADAS would be ready to implement in real vehicles on a closed course at first. Eventually, expanding to highways and other roads.

9.4 In Closing

This dissertation proposes the use of biological principles as an inspiration for the development of connected vehicles (CV). The approach proposed in this work imitates communication and navigation principles found across the animal kingdom. These principles include things such as aposematism, bargaining, and Leuckart's law. This dissertation uses a comprehensive and exhaustive dataset, qualitative and quantitative engineering analyses to achieve the proposed research objectives. The viability of this research has been demonstrated through its results and previous research. Fish and Bras observed optimized impact zones on vehicles (Fish & Bras 2021), and this research targeted impact zones needing improvement for the design of BICADAS. The analyses warrant the expanded implementation of biological principles into the automotive industry. Using biological inspiration fewer crashes can be achieved with the additional bonus of lowering associated costs of technology and crashes. Ultimately, this work will save lives through the adoption of biological principles for the automotive industry.

APPENDIX A. MAPS OF CRASHES

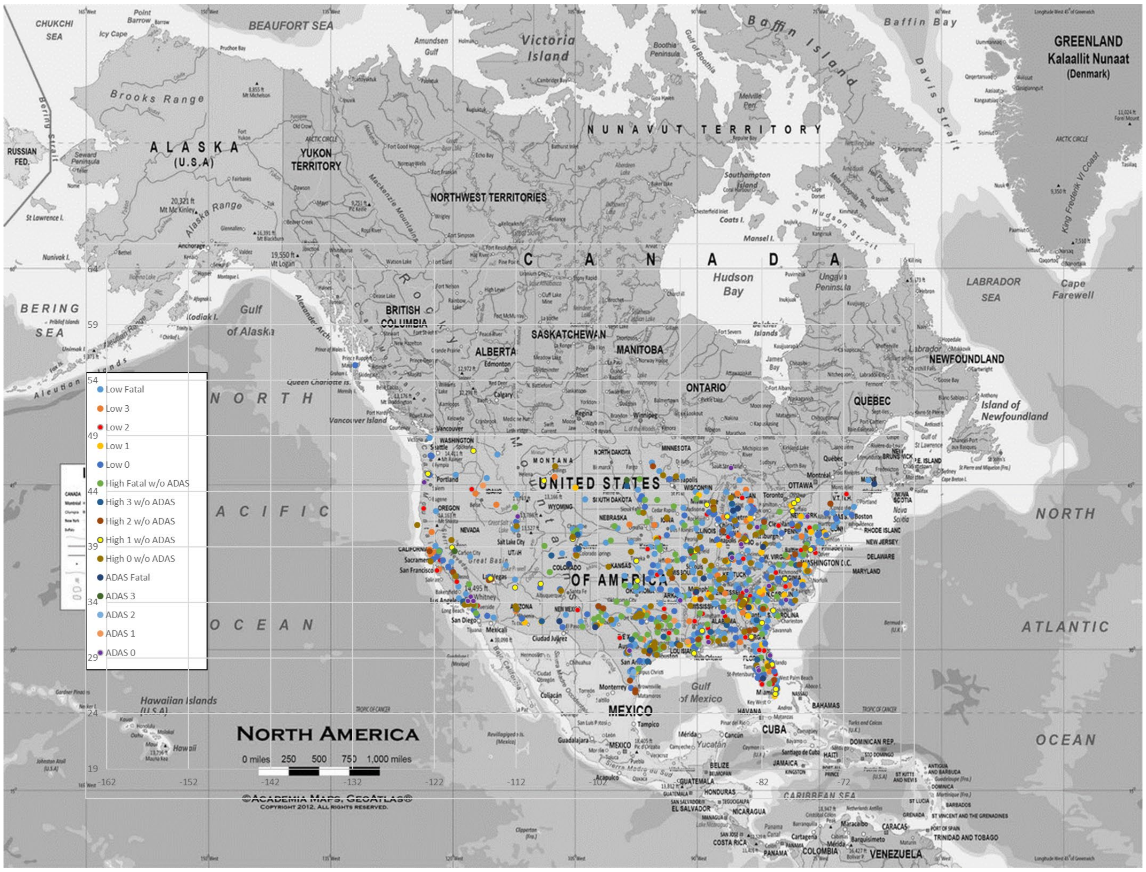

Figure A58: Map of 2017 Ford Accidents based on injury severity in the FSLDPT.

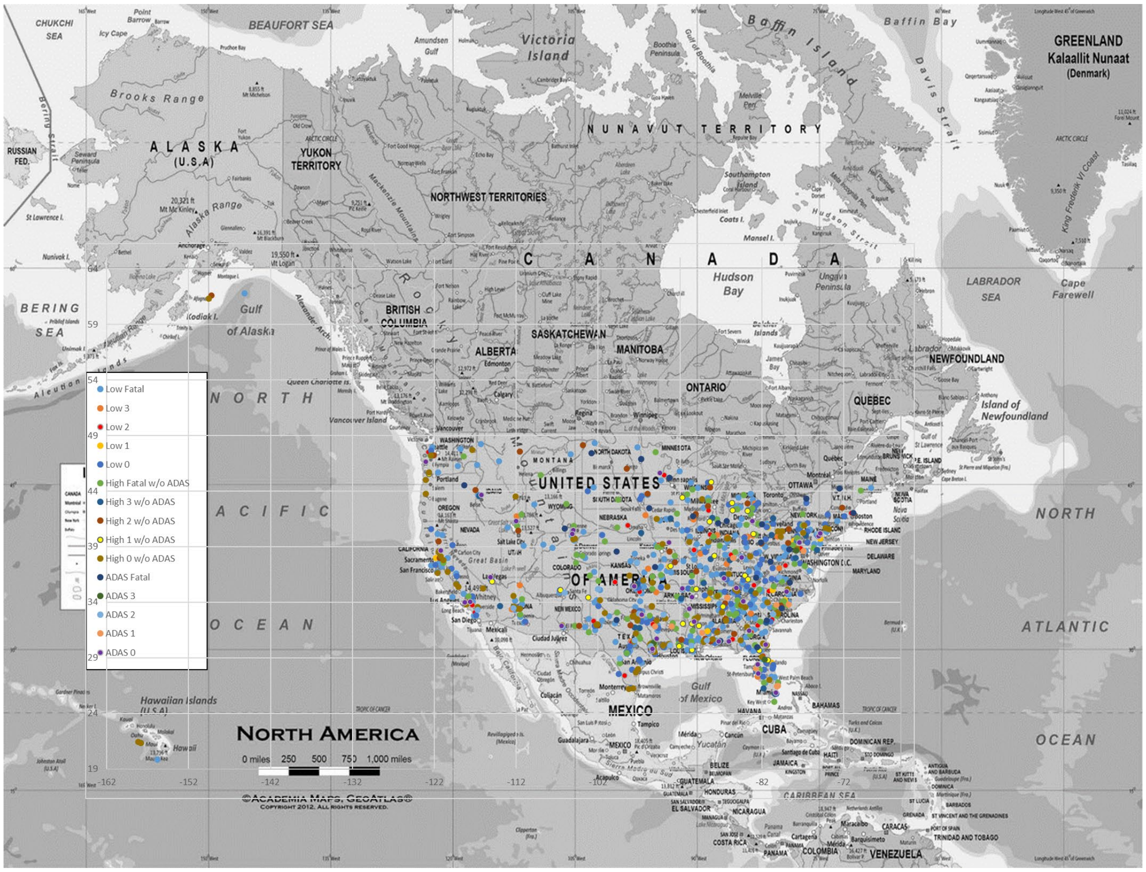

Figure A59: Map of 2018 Ford Accidents based on injury severity in the FSLDPT.

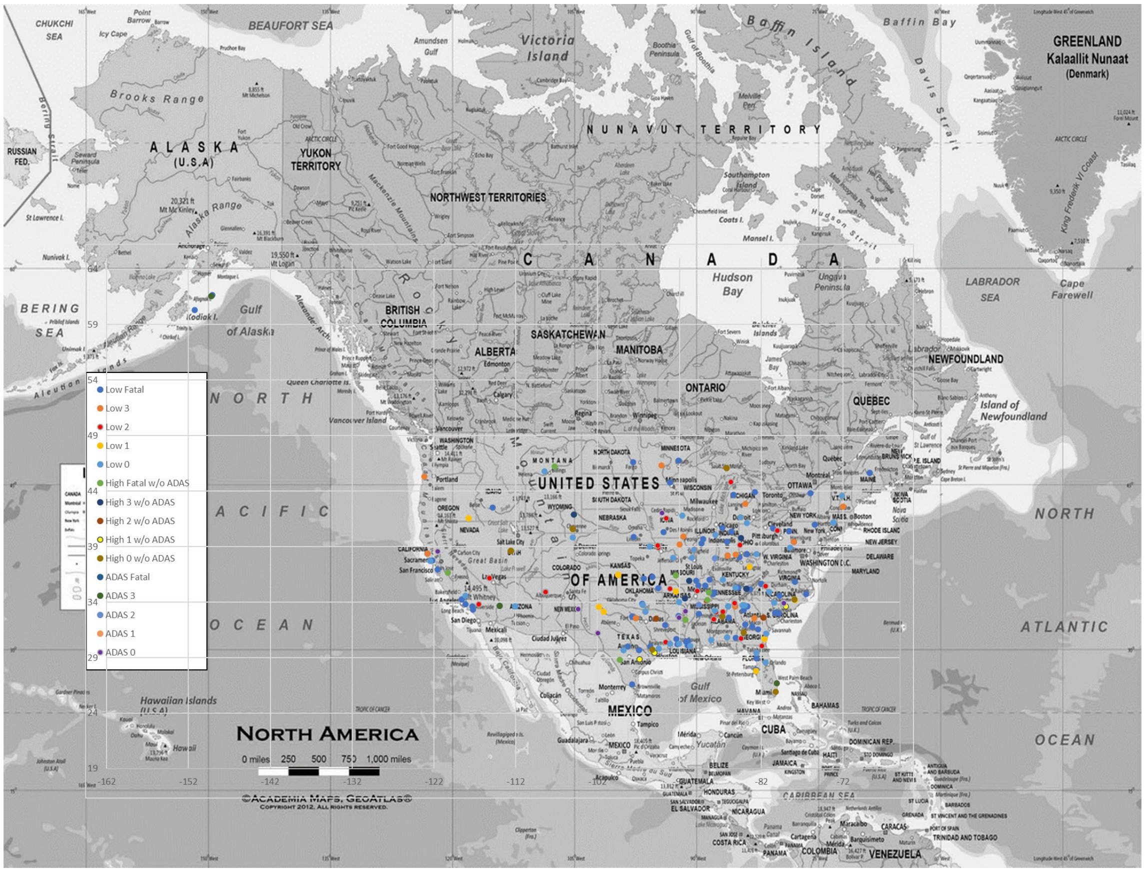

Figure A60: Map of 2016 GMC accidents based on injury severity in the FSLDPT.

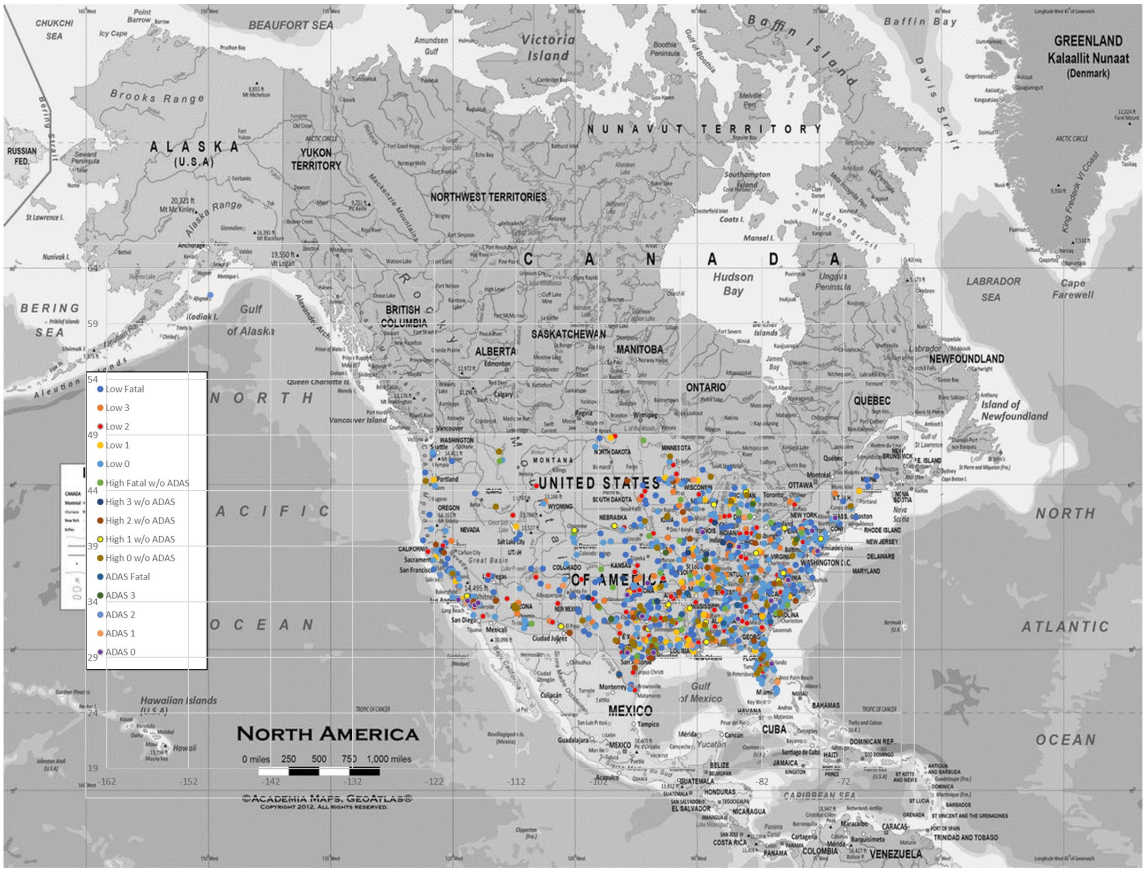

Figure A61: Map of 2016 Chevrolet accidents based on injury severity in the FSLDPT.

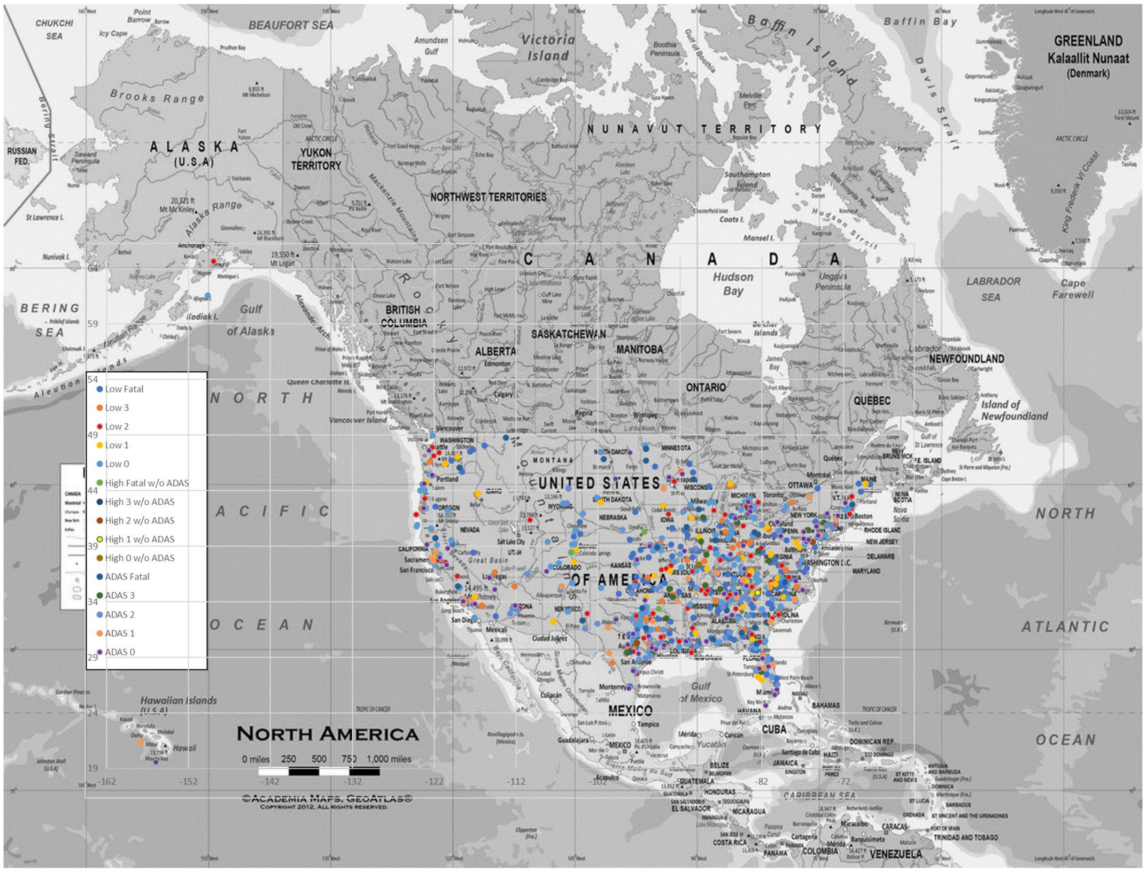

Figure A62: Map of 2016 RAM accidents based on injury severity in the FSLDPT.

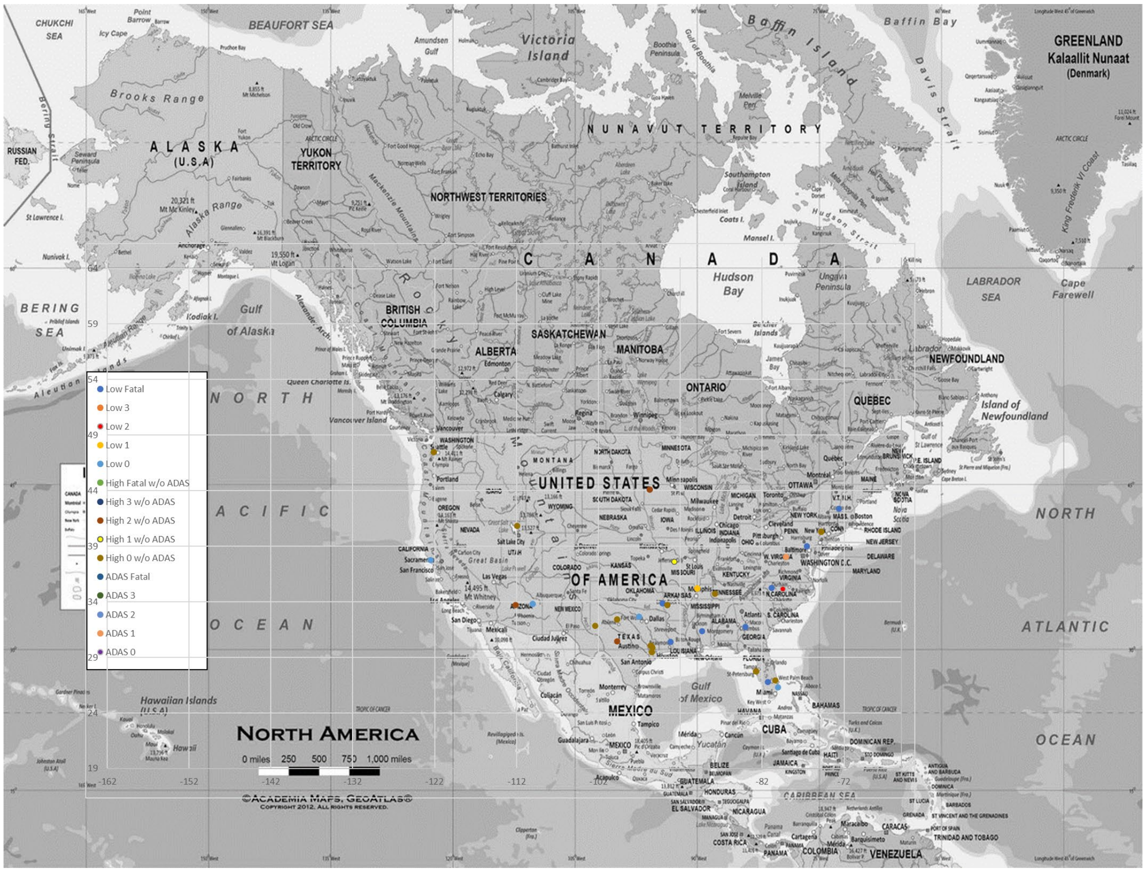

Figure A63: Map of 2016 Toyota accidents based on injury severity in the FSLDPT.

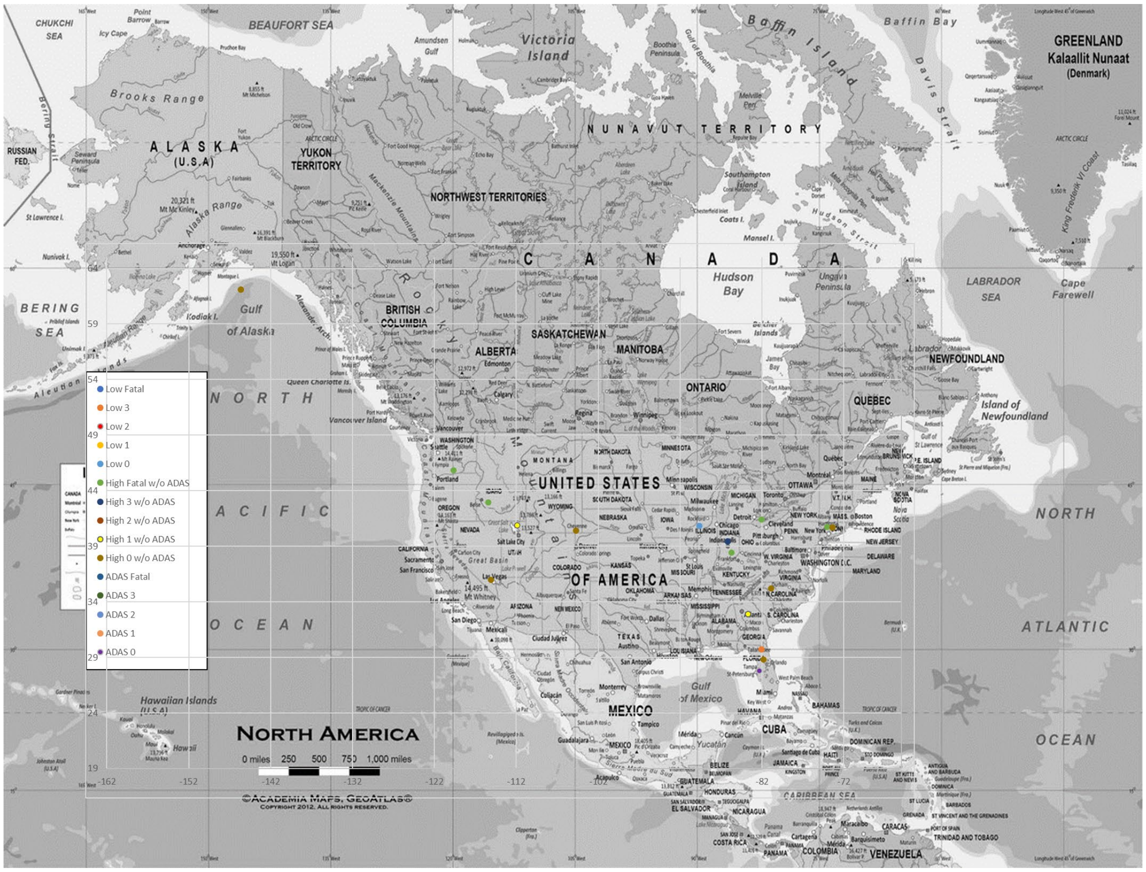

Figure A64: Map of 2016 Honda accidents based on injury severity in the FSLDPT.

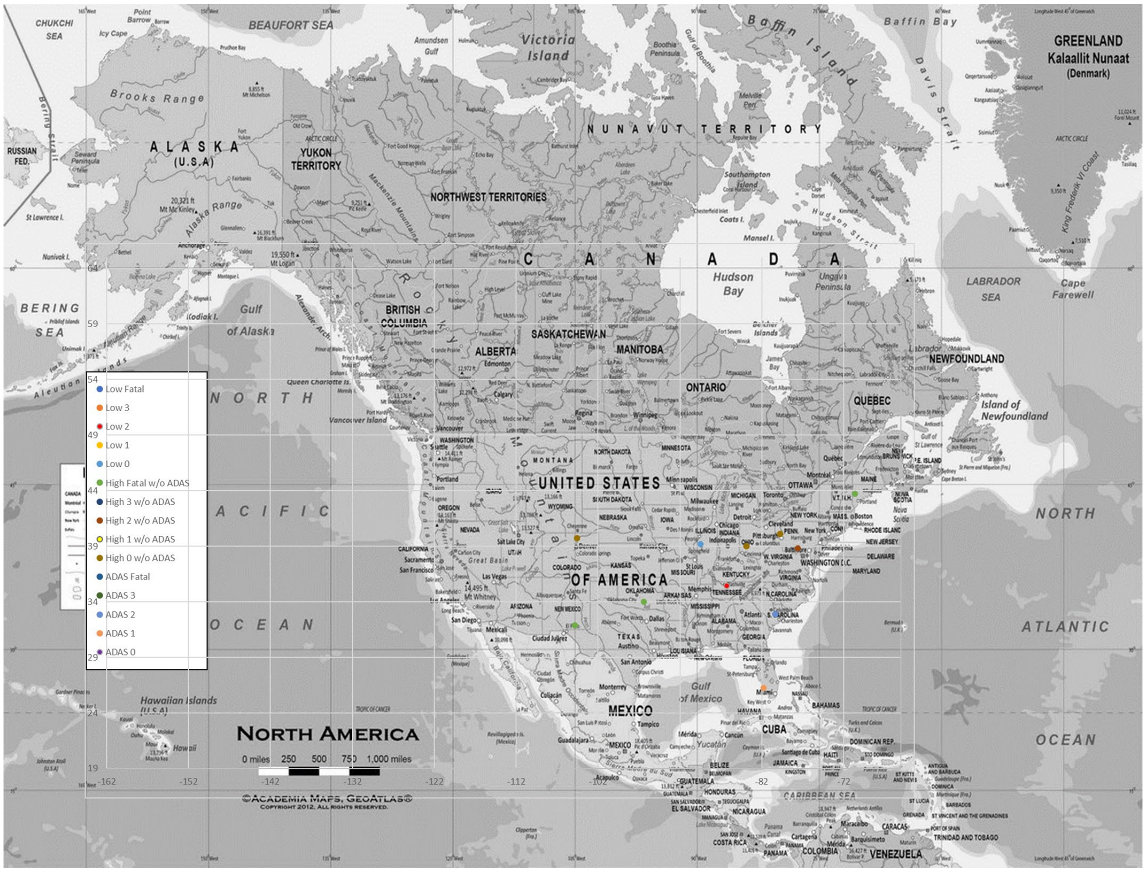

Figure A65: Map of 2016 Nissan accidents based on injury severity in the FSLDPT.

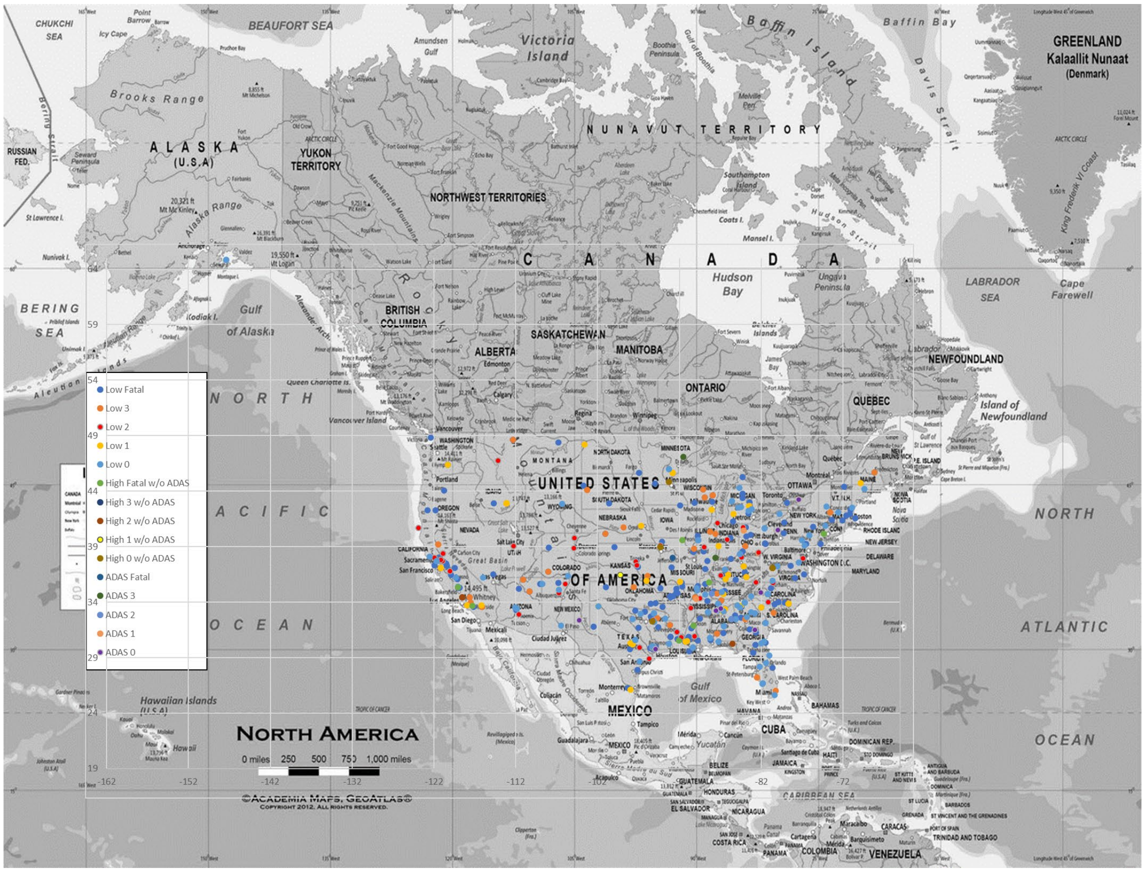

Figure A66: Map of 2017 GMC accidents based on injury severity in the FSLDPT.

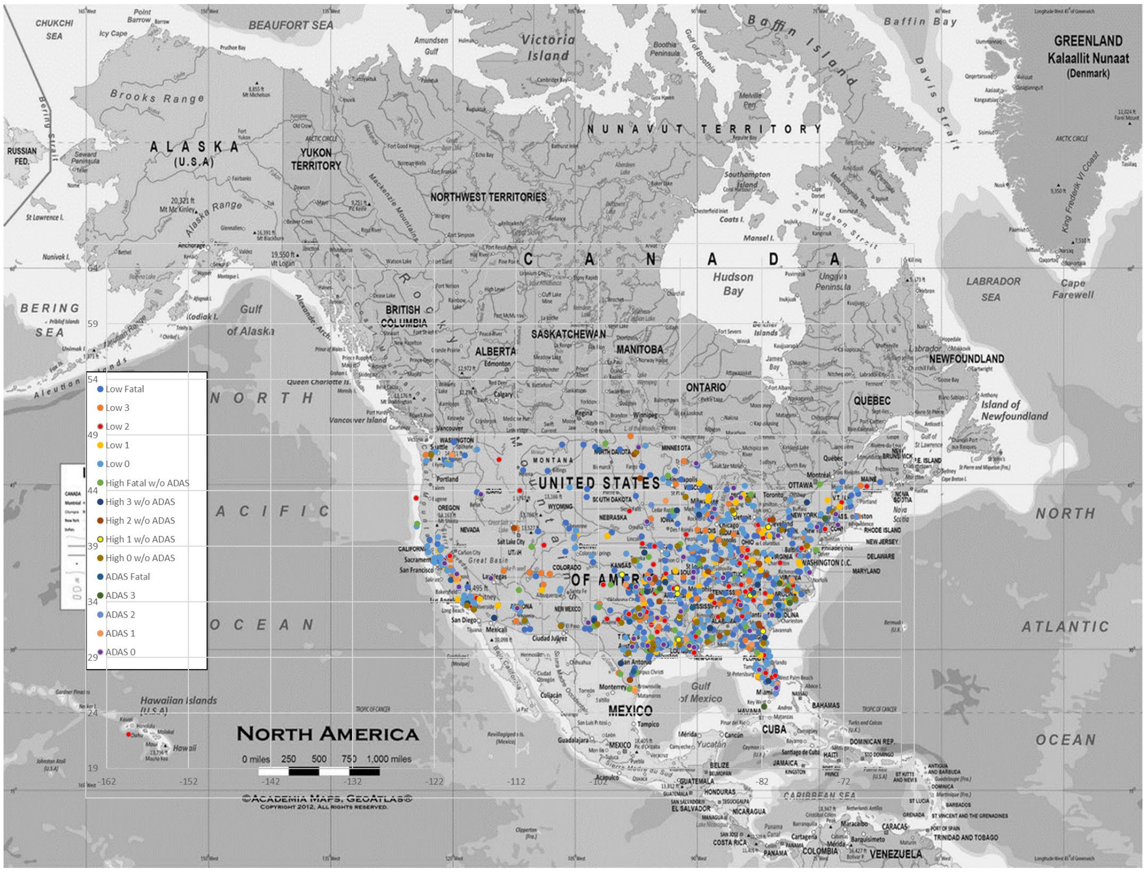

Figure A67: Map of 2017 Chevrolet accidents based on injury severity in the FSLDPT.

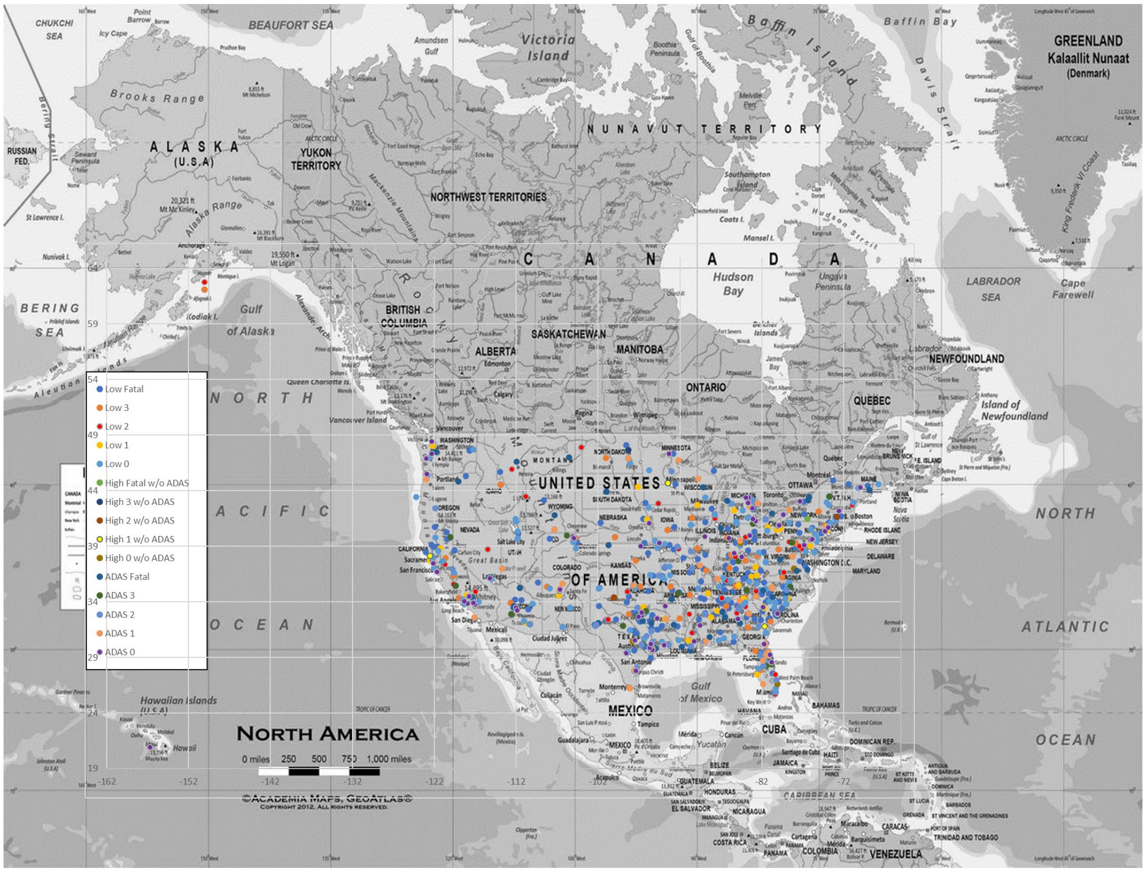

Figure A68: Map of 2017 RAM accidents based on injury severity in the FSLDPT.

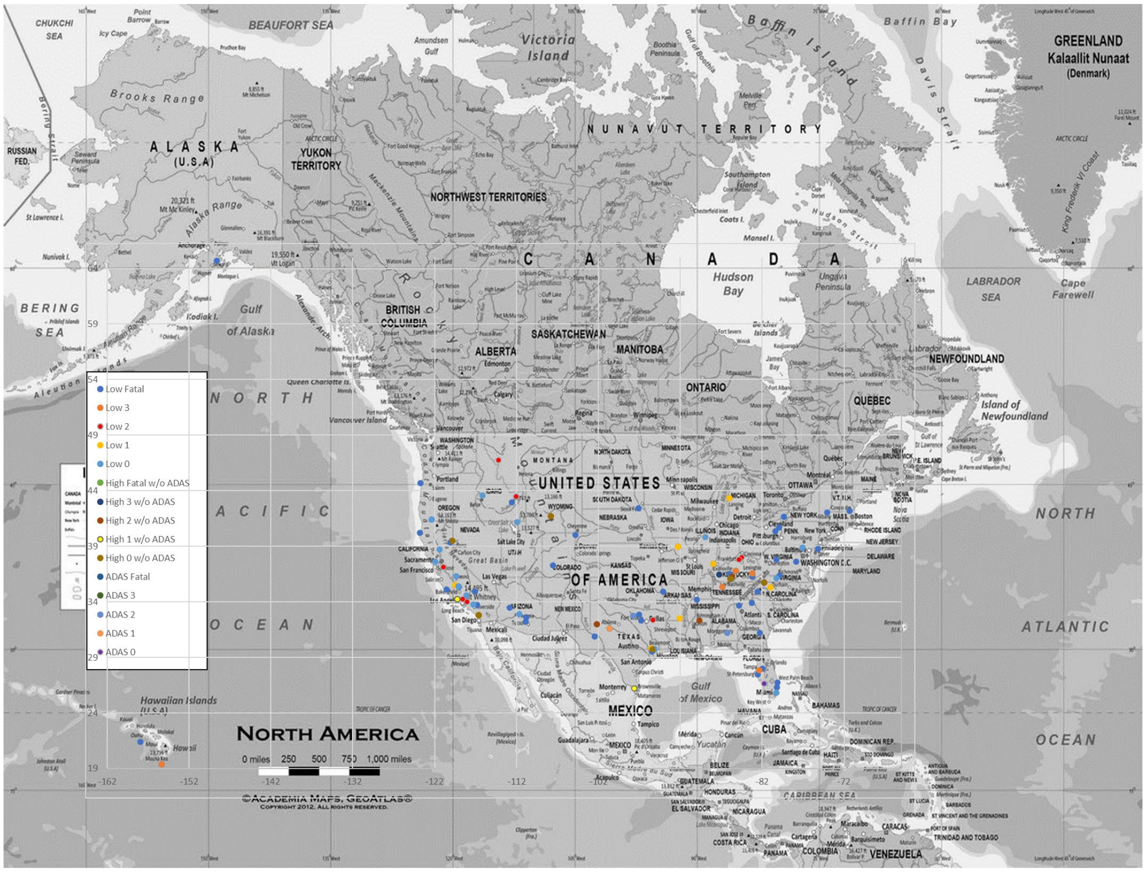

Figure A69: Map of 2017 Toyota accidents based on injury severity in the FSLDPT.

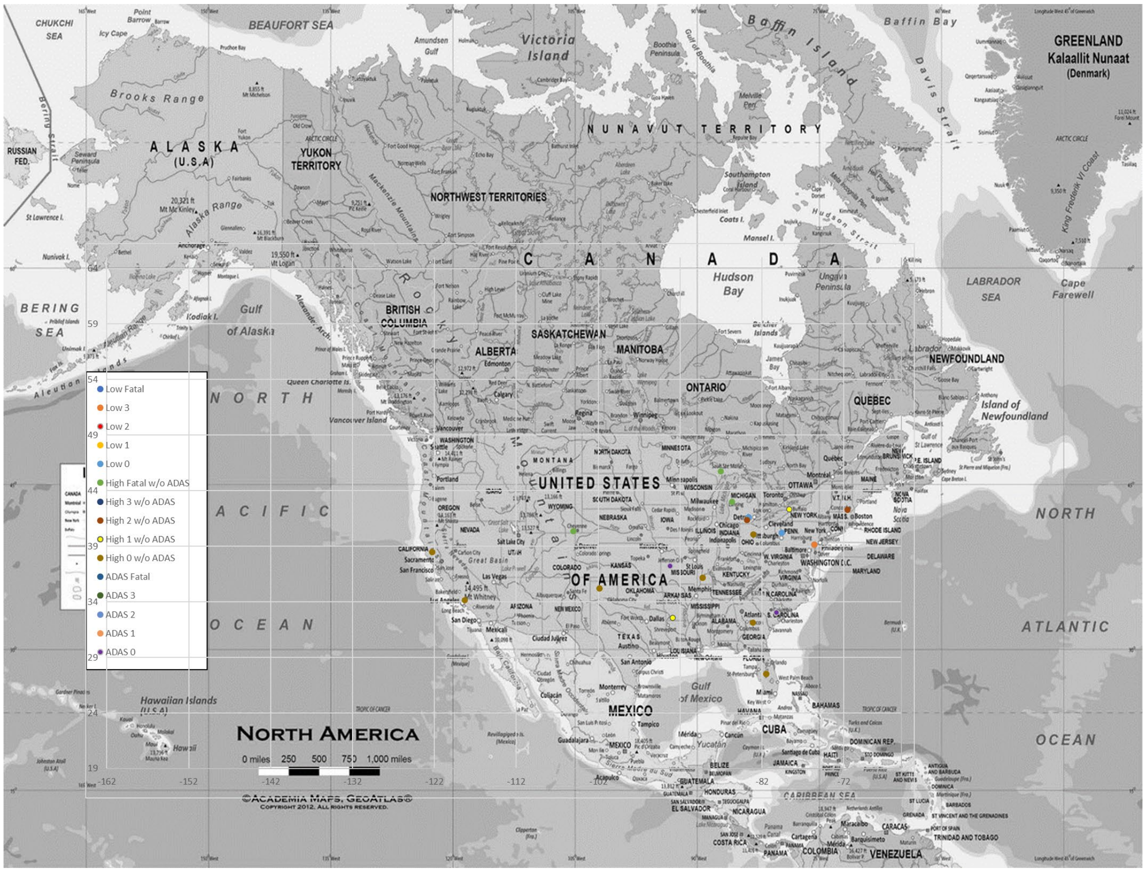

Figure A70: Map of 2017 Honda accidents based on injury severity in the FSLDPT.

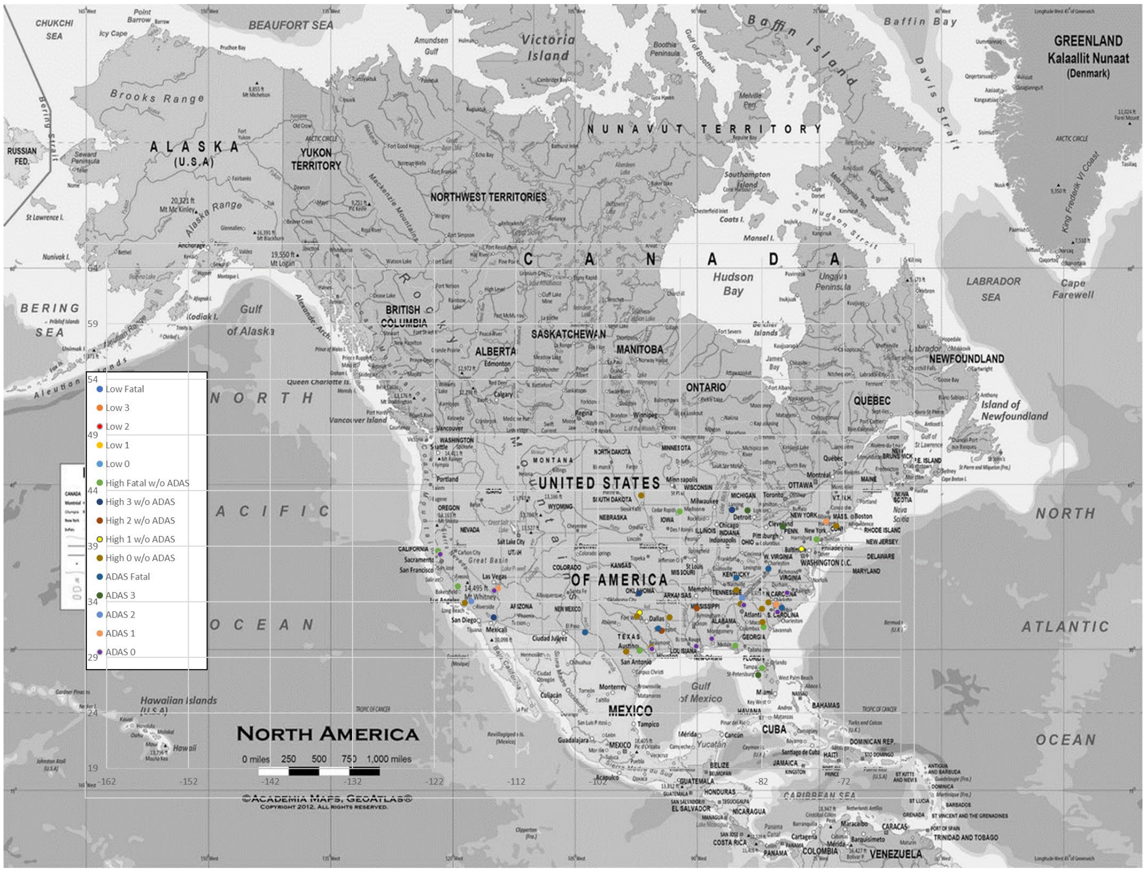

Figure A71: Map of 2017 Nissan accidents based on injury severity in the FSLDPT.

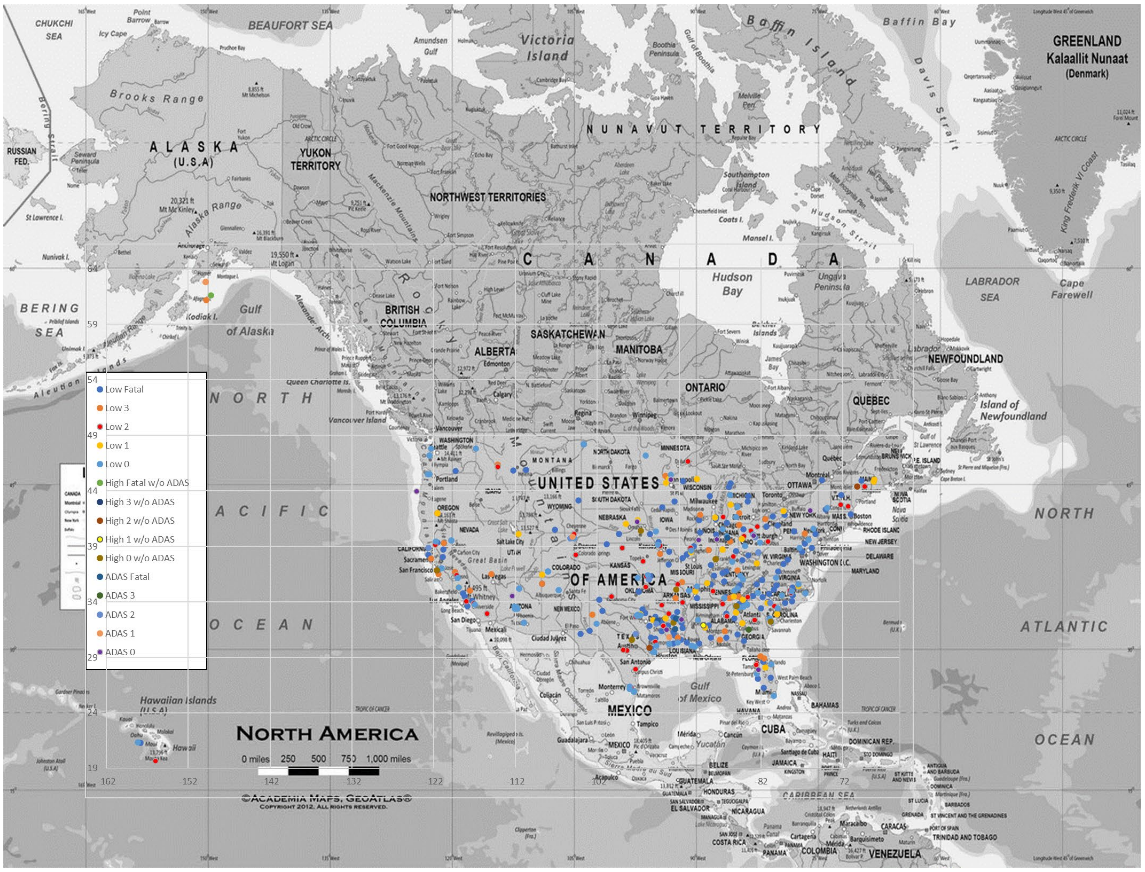

Figure A72: Map of 2018 GMC accidents based on injury severity in the FSLDPT.

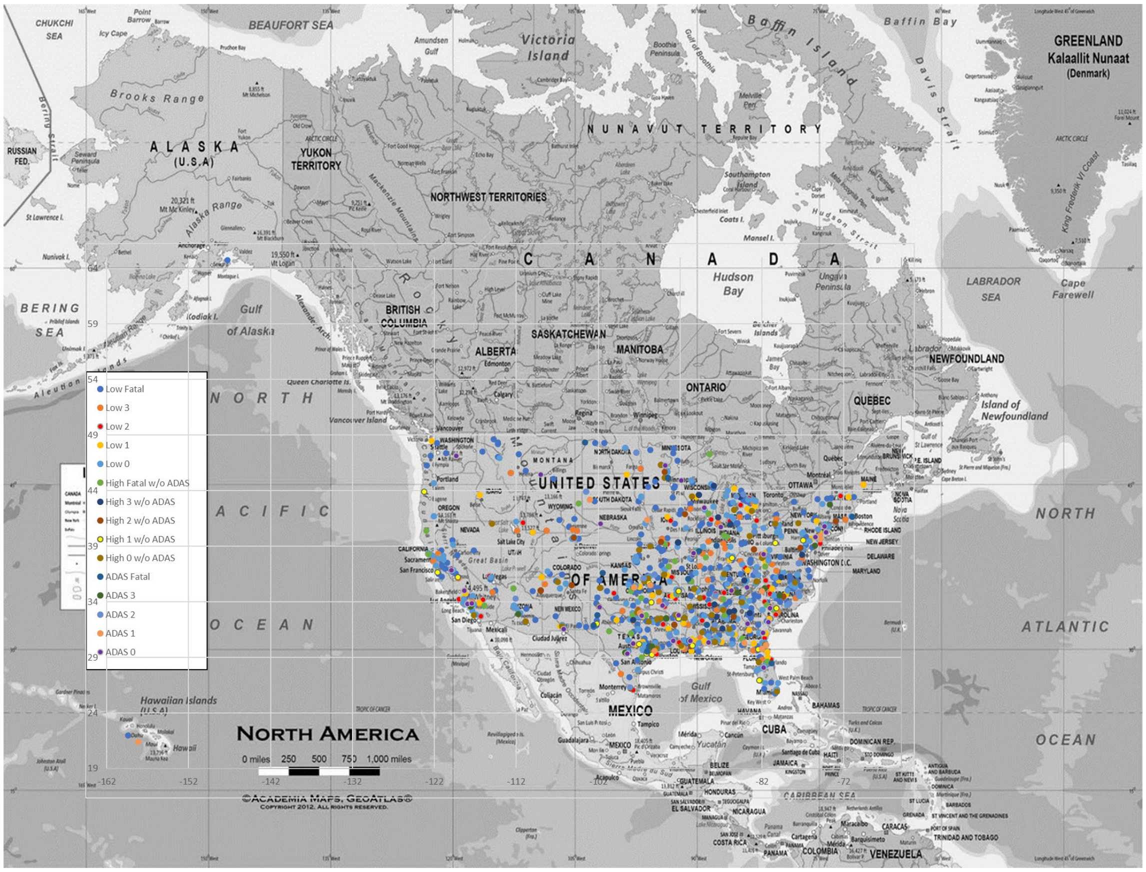

Figure A73: Map of 2018 Chevrolet accidents based on injury severity in the FSLDPT.

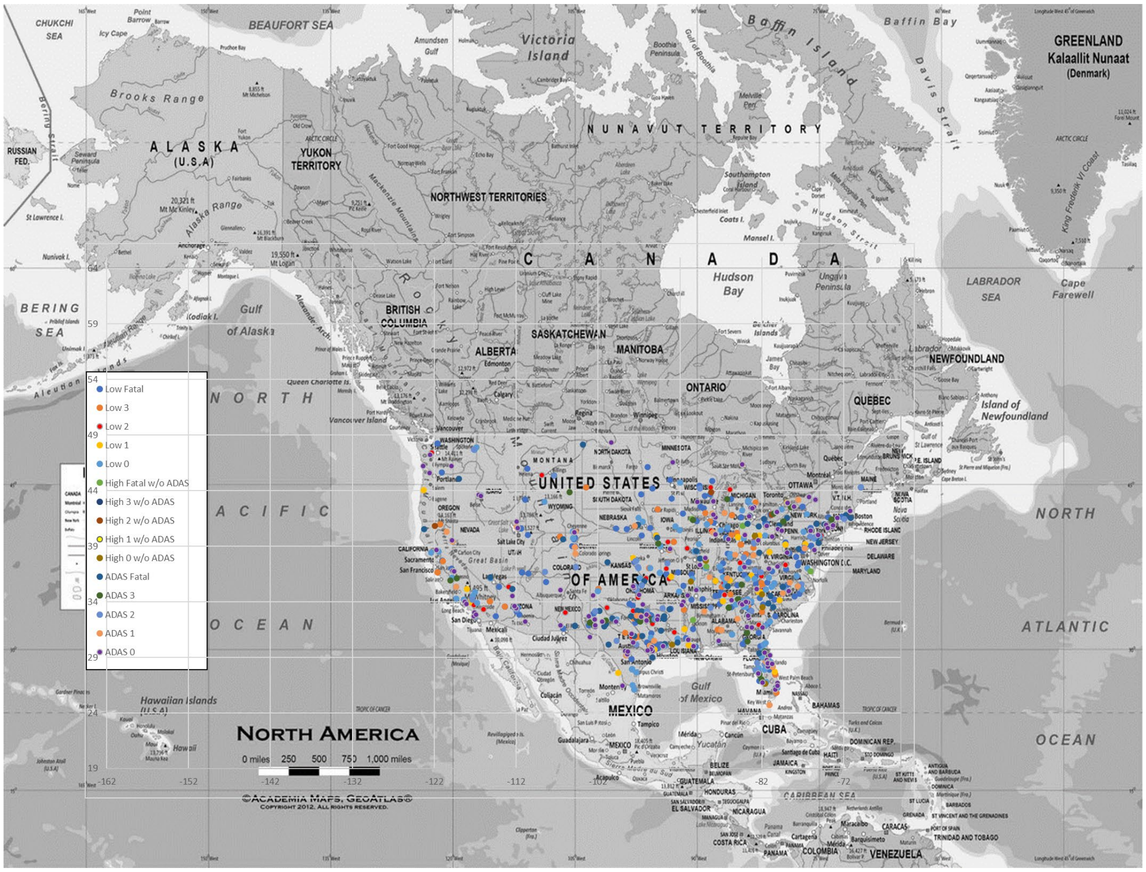

Figure A74: Map of 2018 RAM accidents based on injury severity in the FSLDPT.

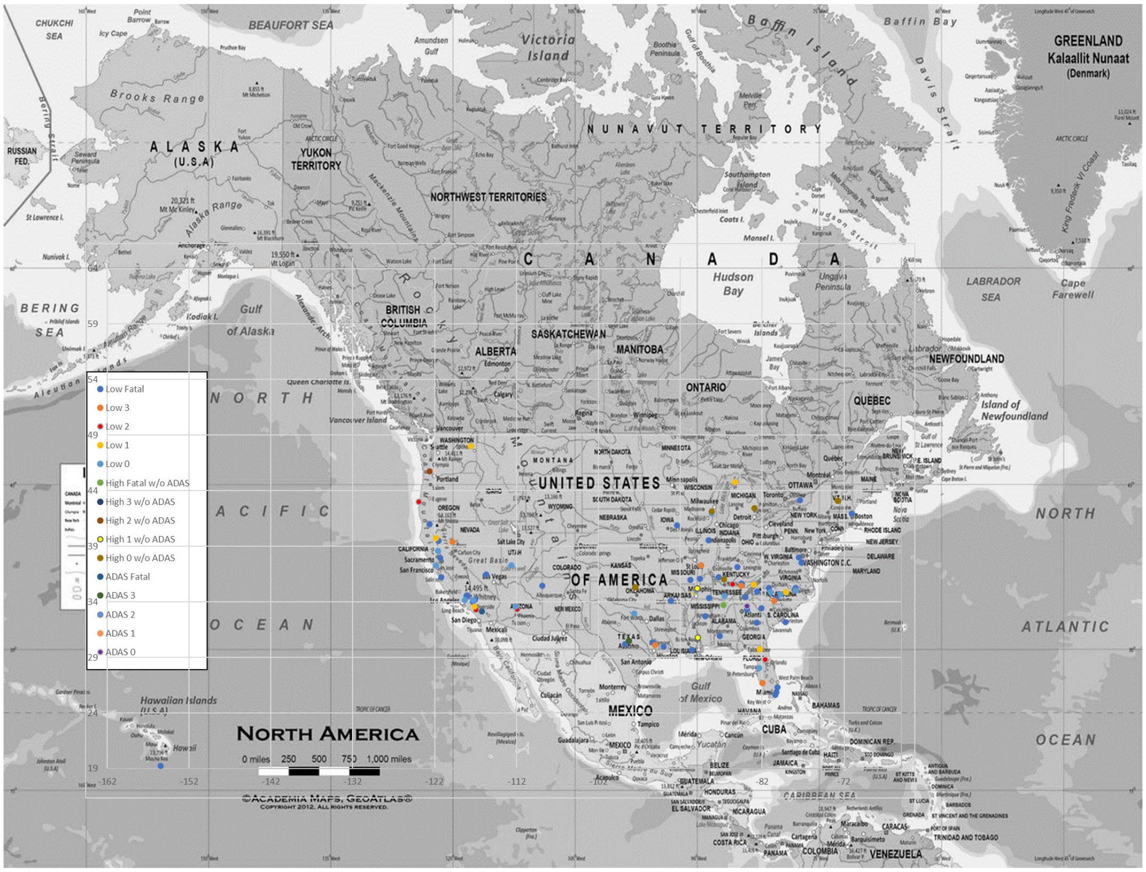

Figure A75: Map of 2018 Toyota accidents based on injury severity in the FSLDPT.

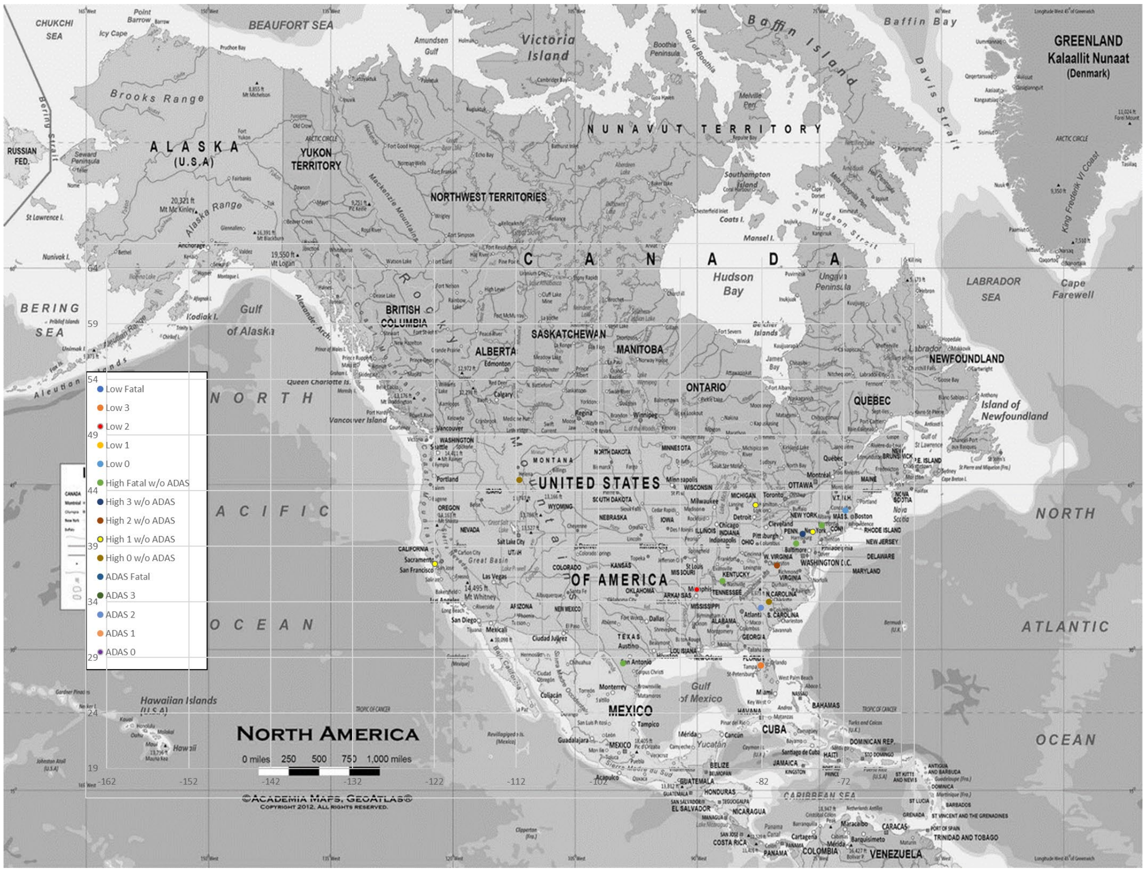

Figure A76: Map of 2018 Honda accidents based on injury severity in the FSLDPT.

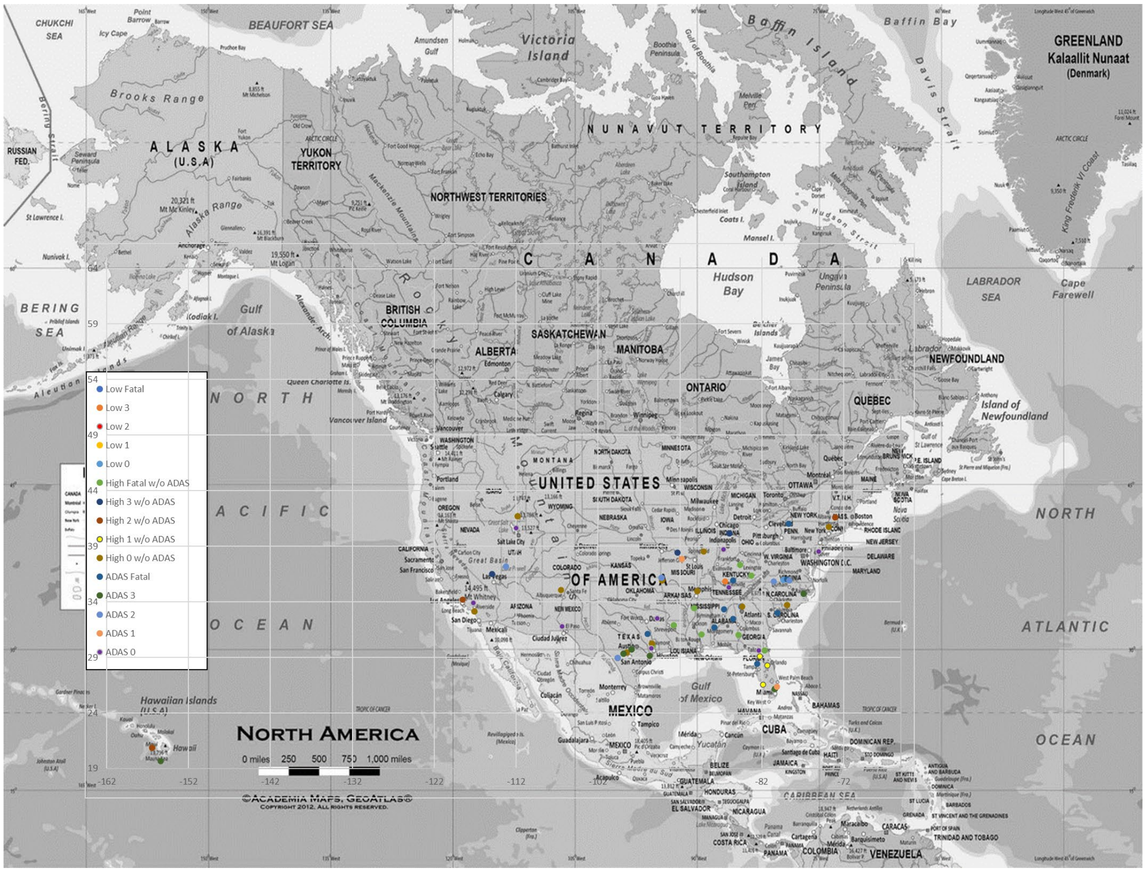

Figure A77: Map of 2018 Nissan accidents based on injury severity in the FSLDPT.

APPENDIX B. GPS AND ROAD VIEWS OF FARS CRASHES

Link to viewable PowerPoint file of visually inspected crashes. If clicking the link does not work, copy and paste it into your web browser.

https://www.dropbox.com/s/kn2koi3xjqy4n8i/Presentation%20of%20Visual%20Inspection%20of%20Fatal%20and%20Non-Fatal.pptx?dl=0

APPENDIX C. JAVA BARGAINING CODE

```
/*
 * To change this license header, choose License Headers in Project Properties.
 * To change this template file, choose Tools | Templates
 * and open the template in the editor.
 */
package connectedvehiclebargaining;
import java.math.*;
import java.util.*;
/**
 ************************Program Description**************************
 * Generates solutions for avoiding a vehicle on vehicle crash using an Archimedean weight optimization.
*
 *
*
```

* //Variable Dictionary//

* a1: [double] is the solved for acceleration of vehicle 1

* a2: [double] is the solved for acceleration of vehicle 2

* acc: [double] is the absolute acceleration that can be achieved in 2 seconds to guarantee the max acceleration is not violated

* acc1: [double] determines the acceleration for vehicle 1

* acc2: [double] determines the acceleration for vehicle 2

* arch1: [double array] in the Archimedean method array of values for previous best solution to compare to arch2

* arch2: [double array] in the Archimedean method array of values for current solution to compare to arch1

* best: [double array] stores the values for the new best solution to the Archimedean comparison

* d: [double] in the velocity method is the initial distance in meters

* dis: [double] initial distance between vehicles 1 and 2 in meters

* dv: [double] is the difference between the two velocities (v1 and v2)

* emv1: [double] emergency vehicle status for vehicle 1 (0 for emergency vehicle, 1 for non-emergency vehicle)

* emv2: [double] emergency vehicle status for vehicle 2 (0 for emergency vehicle, 1 for non-emergency vehicle)

* i: [double] counter in a for loop that runs for the difference between vehicles 1 and 2 velocities

* maxacc: [double] is the max acceleration most vehicles can safely operate at

* solnnew: [double array] array of final velocities and accelerations to be compared in the Archimedean

* solnnull: [double array] is the array set as a baseline for the first Archimedean comparison

* t: [double] global static variable for the max time in seconds needed to avoid a crash for proper spacing

* test1: [boolean] returns true if the acceleration of vehicle 1 is with in a feasible value of 4.6m/s^2

* test2: [boolean] returns true if the acceleration of vehicle 2 is with in a feasible value of 4.6m/s^2

* v1: [double] is the solved for velocity of vehicle 1

* v1i: [double] input of vehicle 1's velocity in mph

* v1ims: [double] converts v1i to meters per second for calculations

* v2: [double] is the solved for velocity of vehicle 2

```
 * v2i: [double] input of vehicle 2's velocity in mph

 * v2ims: [double]  converts v2i to meters per second for calculations

 * value1: [double] value of the Archimedean for the previous best solution

 * value2: [double] value of the Archimedean for the current solution for comparison to previous best

 * vel: [double array] array of the values for the solved for velocities of vehicles 1 and 2

 * vf1: [double] in the velocity method is the final velocity found for vehicle 1

 * vf2: [double] in the velocity method is the final velocity found for vehicle 2

 * vi1: [double] in the velocity method is the initial velocity for vehicle 1

 * vi2: [double] in the velocity method is the initial velocity for vehicle 2

 * w1: [double] weight for the emergency vehicle portion of the Archimedean comparison

 * w2: [double] weight for the vehicle velocity portion of the Archimedean comparison

 * w3: [double] weight for the vehicle acceleration portion of the Archimedean comparison

 *

 */

public class ConnectedVehicleBargaining {
```

```
static double t = 3;


/**
 * //////////////////////// Main Method Description /////////////////////////
 * Calls on other methods to compute optimization for finding final velocities
 * based on vehicle physical limitations, and particle physics. Those values are
 * then passed to the Archimedean to determine if the solution is better than
 * previously found solution.
 */
public static void main(String[] args) {


    //setting initial values for the situation
    double v1i = 50;//vehicle 1 in mph
    double v2i = 90;//vehicle 2 in mph
    double dis = 20;// distance between 1 and 2 in meters
    double emv1 = 1; //0 for emergency vehicle, 1 for none emergency vehicle
    double emv2 = 1; //0 for emergency vehicle, 1 for none emergency vehicle
```

```
// converts speed into meters per second

double v1ims = v1i * 0.44704;

double v2ims = v2i * 0.44704;


double acc1 = AccelerationValue(v1i, v2i);//determine acceleration for vehicle 1

double acc2 = AccelerationValue(v1i, v2i);//determine acceleration for vehicle 2


double solnnull[] = {emv1, emv2, v1ims, v2ims, acc1, acc2}

//Archimedean weights

double w1 = 0.6;

double w2 = 0.3;

double w3 = 0.1;


double best[] = new double[5];


best = solnnull;
```

```
        System.out.println("The initial situation:= emv1: " + best[0] + ", emv2: " + best[1] +
", vehicle 1 initial speed: " + best[2]

                + "m/s, vehicle 2 initial speed: " + best[3] + "m/s, acceleration 1: " + best[4] +
"m/s^2, acceleration 2: "

                + best[5] + "m/s^2");



            double vel[] = Velocity(v1ims, v2ims, dis);

            double v1 = vel[0];

            double v2 = vel[1];

            double a1 = AccelerationValue(v1ims, v1);

            double a2 = AccelerationValue(v2ims, v2);

//          System.out.println("solution new: vehicle 1 speed " + v1/0.44704 + "mph, vehicle
2 speed " + v2/0.44704 + "mph, acc1 " + a1 + ", acc2 " + a2);

            double solnnew[] = {emv1, emv2, v1, v2, a1, a2};



            best = Archimedean(w1, w2, w3, best, solnnew);
```

```
            System.out.println("The solution:= emv1: " + best[0] + ", emv2: " + best[1] + ",
vehicle 1 speed: " + best[2]/0.44704
                + "mph, vehicle 2 speed: " + best[3]/0.44704 + "mph, acceleration 1: " +
best[4] + "m/s^2, acceleration 2: "
                + best[5] + "m/s^2");
    }
    /**
     **********Archimedean Method Description********************
     * Compares two arrays by calculating values based on corresponding weights
     * of each index of the array. The smallest value is returned
     */
    public static double[] Archimedean(double w1, double w2, double w3, double[] set1,
double set2[]) {

        double arch1[] = set1;
        double arch2[] = set2;
```

```
        double value1 = w1 * arch1[0] + w1 * arch1[1] + w2 * arch1[2] + w2 * arch1[3] +
w3 * arch1[4] + w3 * arch1[5];

        double value2 = w1 * arch2[0] + w1 * arch2[1] + w2 * arch2[2] + w2 * arch2[3] +
w3 * arch2[4] + w3 * arch2[5];



//        System.out.println("value 1: " + value1);

//        System.out.println("value 2: " + value2);

        if (value1 <= value2) {

            return arch1;

        } else {

            return arch2;

        }

    }




    /**

     * *********Velocity Method Description********************
```

```
 * Calculates the final velocities for both vehicles for avoiding a crash
 * of the two vehicles.
 */
public static double[] Velocity(double v1i, double v2i, double dis) {

    double vi1 = v1i;
    double vi2 = v2i;
    double vf1 = vi1;
    double vf2 = vi2;
    double d = dis;

    //double vel[]= {vf1, vf2};
    for (double i = vi1; i <= vi2; i++) {

        if ((vf2 - vf1) > (d / t) && Acceleration(vi1, vi2) == true) {
            vf2 = vf2 - 1;
        } else if ((vf2 - vf1) > (d / t) && Acceleration(vi1, vi2) == false) {
```

```
                vf2 = vf2 - 1;

                vf1 = vf1 + 1;

            } else if ((vf2 - vf1) <= (d / t) && Acceleration(vi1, vf1) == true && Acceleration(vi2, vf2) == true) {

                double vel[] = {vf1, vf2};

//                System.out.println("Seen 1 Velocities: " + vel[0] / 0.44704 + ", " + vel[1] / 0.44704);

            }

        }

        double vel[] = {vf1, vf2};

        return vel;

    }


    /**

     **********Acceleration Method Description******************************

     * Determines if the max acceleration of a standard vehicle (4.6 m/s^2) will

     * be violated by the two velocity values entered.
```

```
 */
public static boolean Acceleration(double v1, double v2) {


    double maxacc = 4.6;

    double dv = v2 - v1;

    double acc = Math.abs(dv / 2);// 2 seconds is used for the time to give a factor of
safety of 1.5

//        System.out.println("current acc" + acc);

    if (acc <= maxacc) {

        return true;

    } else {

        return false;

    }

}

/**

 **********Acceleration Value Method Description**************************

 * Calculates the acceleration based on the input velocities.
```

```
 */
public static double AccelerationValue(double v1, double v2) {

    double dv = v2 - v1;
    double acc = Math.abs(dv / 2);// 2 seconds is used for the time to give a factor of
safety of 1.5

    return acc;
}
}
```

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