MOBILITY AND SAFETY IMPACTS OF AUTONOMOUS VEHICLES

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Fasil Sagir

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THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF APPROVAL

Dr. Satish V. Ukkusuri, Chair

Lyles School of Civil Engineering

Dr. Shreyas Sundaram

Department of Electrical Engineering

Dr. Gregory Shaver

Department of Mechanical Engineering

Approved by:

Dr. Dulcy M. Abraham

Head of the School Graduate Program

To Dad, Mom, Molu and my wife, Anamika: My pillars, my archangels, my world.

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SYMBOLS

v	Speed
t	Time
a	Maximum acceleration
b	Desired deceleration
s	space headway
s_0	Jam distance
Δv	Speed difference between follower and leader
c	Coolness factor
T	Time headway
s^*	Desired headway
Δy	Change in y coordinate of the vehicle in a single time step
Δx	Change in x coordinate of the vehicle in a single time step
θ	angle (in radians)
p	Politeness factor
Δa_{thr}	Acceleration threshold
Y_t	Lateral position at time t

ABBREVIATIONS

SAE	Society of Automotive Engineers
AV	Autonomous Vehicles
CV	Connected Vehicles
IDM	Intelligent driver Model
EIDM	Enhanced Intelligent driver Model
MOBIL	Minimizing Overall Braking Induced by Lane Changes
DSRC	Dedicated short-range communications
TTC	Time To Collision

ABSTRACT

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Connected and Autonomous Vehicles (CAV) are revolutionizing the automotive space. We are at the cusp of a, once in a century, transformation in the automotive space. This work strives to understand, analyze and provide insights on the various dimensions this transition is going to impact. We begin with the exploration of the CAV landscape which is in a continuous state of flux. We attempt to examine, analyze and evaluate this space using semi-structured interviews with experts from across the whole country. The interviews are supported additionally by survey questions which further capture the expert views quantitatively. This initial exploratory study leads us to the central questions of this study which include (1) Modeling of SAE (Society of Automotive Engineers) vehicles from level 0 to level 5 using a simulation framework (2) Analysis of mobility and safety impacts of SAE vehicles. (3) Building a predictive model of the risk level of autonomous vehicles based on trajectory information.

For the modeling of AVs, the different levels of SAE were mapped to particular functionalities. Each of these functionalities were then modeled using the external driver model (EDM) and were tested on VISSIM to evaluate their performance. The mobility impacts of these models were tested on a highway and an intersection environment. The analysis were conducted for 100% penetration levels for each SAE and also for different penetration levels

One of the most important benefits of AVs that has been touted by OEMs and DOTs alike, are the safety benefits of CAVs. Among many industries which will be affected by the safety aspects of CAVs, insurance industry is one of them. An immediate challenge that lies in front of them will be to evaluate the risk level of different SAE classes of vehicles. This will be especially true as most of the SAE level data is unavailable or very scarce. To overcome this limitation, we propose a novel methodology to identify risky driver behavior for every SAE level. The framework includes the utilization of surrogate safety measures modified for SAE levels. The trajectory data created from SAE level simulation is used as the data set for model training and testing which predicts driving risk. The models evaluated are logistic regression, decision trees and neural networks. This framework provides a foundation for modeling the riskiness of autonomous vehicles in traffic networks.

1. INTRODUCTION

1.1 The Connected and Autonomous Vehicles Era

Connected and autonomous vehicles (CAVs) are an emerging technology that offer the potential to dramatically improve multiple facets of transportation. These technologies are rapidly maturing, and the time line for their wider deployment is currently uncertain. Despite the uncertainty, these technologies are expected to bring about numerous societal benefits, such as enhanced traffic safety, improved mobility and reduced fuel emissions.

As the oncoming autonomous wave approaches, there still needs to be a deeper analysis and evaluation of the impacts that they will have on various aspects especially in the direction of mobility and safety which are the among the biggest benefits expected of them.

1.2 Rationale for the study

The ever changing landscape of AVs needs to be examined as the key to the future directions lies in the current emerging themes of autonomy levels, transportation-as-a-service, interplay of autonomy and connectivity, new entrants in the automotive space among other powerful ideas. The impact on Federal and State transportation agencies, Original Equipment Manufacturers and motor insurance firms is expected to be immense given the fact that this is a once in a century change in the automotive space. There is a need to understand the issues from transportation planning and automotive business point of view to understand the impacts more accurately and in depth.

Especially, in the light of current evolution of the space where every manufacturer is coming up with various autonomous capabilities in their vehicles, there is a need to categorize these capabilities and come up with a framework which analyze their category level impacts.

In order to address the issue of categorization, Society of Automotive Engineers (SAE) came up with the definition of different levels of autonomy. These definitions identify the various autonomous levels based on who is responsible for steering, acceleration, monitoring of environment and fallback performance of dynamic driving task. NHTSA initially came up with its own definitions of the autonomy levels but later in the FAHV published in 2017 adopted SAE levels of automation. These levels range from 0 (no automation) to 5 (fully autonomous).

Even though there are multiple works which have modeled autonomous vehicles but previously there has been very limited work on SAE level modeling of autonomous vehicles and evaluating the impacts on mobility and safety.

1.3 Objectives

The objectives of the study are as follows

1. Analysis of the CAV landscape analysis
    (a) Understand from the technical experts and thought leaders the evolution of the CAV environment. This will be done using quantitative surveys and semi-structured qualitative detailed interviews.
    (b) Cover a wide range of stakeholders, from private to public domains which has not be attempted before and hence will contribute to a 360 degree understanding of the landscape.
2. Modeling of SAE levels
    (a) Modeling of each SAE level (0-5).
    (b) Modeling philosophy to use a a bottom-up approach.

(c) Impact analysis of SAE levels using traditional and non- traditional mobility measures.

(d) Penetration studies to evaluate the mobility impacts of various SAE volume mixes.

3. SAE safety analysis and prediction

   (a) Safety impact analysis of each SAE level.

   (b) Build a prediction model which classifies each driver into various risk categories for every SAE level.

1.4 Outline

In chapter 1, we look at the CAV landscape and analyze it through a two step process which includes 32 semi- structured interviews followed up by quantitative surveys questions. The questions for interviews and surveys were from two catagories: (1) Organization related (2) CAV related. Experts from industry, academia and transportation agencies were contacted and scheduled for interviews.These stake holders analyzed comprised of federal agencies, state agencies, OEMS, highway operators, application developers, research institute, universities, transportation consulting firms and investment firms. The semi structured interviews revolved around the following topics.

1. Organization related

   (a) Objectives

   (b) Opportunities

   (c) Threats/ Challenges

2. CAV related

   (a) Interplay of connectivity and autonomy

(b) Evolution of CVs

(c) Evolution of AVs

(d) Infrastructure requirements

(e) DSRC vs. 5G

(f) Need for standardization for connected vehicles

(g) Need for standardization for autonomous vehicles

The objective of this chapter is to expand on prior CAV works by conducting extensive interviews and surveys with CAV technical professionals and thought leaders. CAV opinions contributed by these individuals will fill the existing void, allowing for more informed decisions on CAV matters in the future.

In Chapter 2, we propose a novel bottom-up approach to model various SAE levels on VISSIM in a two lane highway environment featuring an on-ramp. The SAE levels have their features automated based on the level of autonomy. We built these models using VISSIM as the platform and integrating various car following, lane changing and lane centering models using the external driver model API.

The mobility impacts of each of the above levels in terms of velocity profiles, lateral position and speed improvements due to superior lane changing algorithms was analyzed. This was done for 100% penetration and for various other penetration levels. Mixed traffic analysis was done to analyze the impact of interactions between various SAE levels.

In Chapter 3, we propose a unique method to identify and predict risky driving behaviour for different SAE level vehicles by using trajectory information. A novel framework is provided in the absence of data for autonomous vehicle related trajectory information. We combine microsimulation and surrogate safety measures to identify conflicts and thereby deduce risky behavior among autonomous vehicles. The trajectory taken as output from the VISSIM simulation is provided as input into SSAM which is the software used to identify conflicts designed by FHWA. Using the conflict information we build a model which can identify risky behavior among AVs using

GPS trajectory information. Using the simulation dataset which comprises of GPS trajectory and risk labels we test different machine learning models. Once tested we compare the results for each SAE level vehicle type. Finally, using this methodology we identify the model which accurately predicts risk for SAE level vehicles.

2. EXPLORATION OF CONNECTED AND AUTONOMOUS VEHICLES LANDSCAPE

2.1 Introduction

Connected and Autonomous Vehicles (CAVs) will improve upon the safety, efficiency, and economics of conventional automobiles [1] - [4] . CAV technology has the potential to save tens of thousands of lives on an annual basis through minimizing human error in driving [5]. Also, CAV technology will enable coordination between vehicles through cooperative cruise control and vehicle platooning [6], [7]. This will increase vehicle density levels and decrease congestion, which has the added benefit of improving mobility. Lastly, CAVs will provide mobility to segments of the population incapable of driving themselves, such as the visually-impaired and elderly, through private ownership and ride sharing in the form of robo taxi services [8], [9].

Given the potential CAV benefits, the automotive industry is prone to disruption by CAV ventures. Full autonomy will alter the nature of the industry by eventually rendering manually-driven cars obsolete [10]. As a result, traditional automakers will have to increase innovation and develop AVs themselves to remain competitive. Furthermore, ride sharing is becoming increasingly prevalent. Autonomous vehicles will expand the disruption brought about by Uber and Lyft to automotive companies themselves, as more vehicle sharing will occur. In addition, CAVs will increase the importance of data in automobile operation. Using the connected vehicle technology and the Internet of Things (IoT) framework, cars will be able to share information with each other, improving driver awareness and creating a big data ecosystem for vehicles [10]. This ecosystem will create a new source of revenue and attract new competitors into the industry, including Google, Apple, and Intel. To clarify, the term CV is used to represent connected vehicles utilizing V2X (vehicle to everything) technologies and the term connectivity is used in relation to V2X technology in the vehicle [11].

The magnitude of the changes brought upon the automotive industry by CAV technology necessitates the implementation of non-traditional practices by emerging and established automotive organizations. These include greater investments in research and development by automotive organizations and collaboration between automotive firms to increase the collective effectiveness of CAV technology. To make informed decisions on how to employ these practices, OEMs, State DOTs, consulting firms, applications developers, and other organizations must develop a comprehensive understanding of the CAV space. This includes knowing the potential benefits, impacts, developmental paths and suitability of CAV applications. This will allow them to maximize the results generated by investment in CAV technology.

This understanding of the CAV space is necessary for any firm's future success in the automotive industry, as it will allow for sound strategic and tactical decisions-making in a fast-changing industry. Consequently, it will be able to utilize CAV technology to generate results from a business perspective over the long term. If this is not accomplished, regardless of the firm's size, it may fall behind due to an absence of innovative products. For relevant stakeholders- OEMs, State DOTs, consulting firms, applications developers, and other organizations- a comprehensive understanding of the CAV space will allow it to innovate effectively and keep pace with industry disruptors such as Google and Uber. To achieve future success, a firm must know what scope and time line CAV development will take. Knowing how CAVs will impact the automotive market is critical because it will allow a firm to use the technology towards establishing a stable position relative to its competitors. Moreover, the state of CAV regulatory legislation must be known. This will allow for an understanding of whether a lack of standardization will pose challenges to CAV development. There are no definite answers to these questions. However, having an informed opinion on them will allow automotive firms to understand the impact CAVs will have on stakeholders, guiding future policy decisions as a result.

Answers to the questions by CAV technical professionals and thought leaders have not been made widely available. These answers are extremely important because these individuals are making design decisions regarding CAVs and supporting infrastructure, heavily influencing the technology's developmental trajectory. Literature review of previous studies reaffirms that there is a lack of collected opinions from individuals with CAV technical or thought leadership backgrounds. Consequently, this study makes a significant contribution by thoroughly collecting the opinions of CAV technical professionals and thought leaders from all regions of the United States. This array of diverse perspectives is intended to serve as an important set of considerations and guidelines for future decisions on CAV matters.

2.2 Literature review

In the past, there have been numerous qualitative publications based on results gathered from survey-driven data and individual interviews relevant to connected and automated vehicles (CAVs). These works assessed public and executive attitudes towards the technology. Public attitudes towards CAV technology were investigated in several past survey and interview-based studies. Howard and Dai conducted surveys in a group classroom setting with likely AV adopters in Berkeley, CA as part of a case study [12]. Adopters' attitudes towards the technology were evaluated through a questionnaire administered in conjunction with unbiased videos highlighting benefits and drawbacks of CAV technology. A work by Virginia Tech sought to collect generational data on attitudes towards advanced vehicle technologies. Drivers across the United States were surveyed [13]. Zmud and Sener evaluated Austin, Texas residents' attitudes towards autonomous vehicles. Residents were surveyed on their intent to use AVs [14]. Individuals who indicated an intent to use self-driving vehicles were interviewed in person to provide further detail.

McKinsey & Company surveyed individuals from Germany, the USA, and China who had recently purchased a vehicle to evaluate public opinions on CAV data privacy

[15]. The survey allowed for a cross-cultural comparison of results. Nordhoff, Van Arem, and Happee synthesized past works on consumer attitudes towards automated driving [16]. The key contribution made was bringing a vast array of study findings together into a single study. Works from institutions and organizations such as the University of Michigan and J.D. Power and Associates were included in the study by Nordhoff et al.

Executive attitudes towards CAV technology were also evaluated in several past survey-based studies. Law firm Foley Larder LLP conducted a survey of international automotive executives on the predominant legal and business issues influencing the development of CAV technology in the present and future [17]. Furthermore, with a digital questionnaire that pertained to the benefits of CAV technology, McKinsey Company collected the opinions of automotive executives on the effects of digitization, connectivity, autonomous driving, and software development [15]. The executive survey indicated automotive executives' sense of impending change in their industry and their recognition of new challenges related to this change.

The role of Cost-Benefit Analysis (CBA) in the decision-making process for infrastructure projects in the Netherlands was evaluated by Mouter and others [18]. Key individuals in the Dutch CBA field were interviewed. Most of these experts filled out a written questionnaire providing additional information on topics of interest. Although not directly CAV-focused, Mouter's publication has the potential to be applicable to future CAV-related ITS projects that are evaluated with CBA.

While many contributions were made to the CAV field by the above publications, they largely ignored a critical source of information. Past surveys and interviews have acquired public and expert opinions on CAV issues from a wide variety of regions and at various sample sizes. However, individuals with CAV technical and thought leadership backgrounds – those working for OEMs, State DOTs, consulting firms, applications developers, financial institutions and other organizations – have been sparsely covered. Furthermore, the means for acquiring information from the public and executives has been primarily survey based. Detailed interviews collecting CAV opinions and knowledge are extremely rare based on the conducted literature review.

This work contributes immensely to several underrepresented sources of CAV information. First, it will contribute to knowledge about CAVs from technical and thought leadership perspectives. Also, this knowledge will be obtained from the two-step perspective of quantitative surveys and qualitative detailed interviews, each of which allows for a wealth of opinions and information to be extracted from every technical expert and thought leader. These interviews and the surveys will contribute a 360-degree technical and thought leadership perspective due to them including the opinions of OEMs, State DOTs, consulting firms, applications developers, and other organizations. Because of this contribution, the current knowledge gap between public perceptions of CAVs and the corresponding industry beliefs will be bridged, allowing for more informed CAV-relevant decisions to be made by public and private organizations in the future. Moreover, the interviews are based on a partially structured interview process. This allowed for responders to answer from a personal perspective. Furthermore, the range of stakeholders that were surveyed and interviewed, from private to public domains is extremely rare.

2.3 Methodology

The motivation behind this study is to understand the current and expected state of Connected and Autonomous Vehicle (CAV) development in the United States. This was accomplished by following a two-fold approach wherein both interviews and surveys are used as means to get the stakeholders' perspectives. It must be noted that, although CAVs are used as a single term for convenience in this study, AVs and CVs are treated separately for analysis when required.

To set the context of this study, it must be noted that a contribution of our work rests in the semi-structured interview methodology employed in our research. These detailed, partially structured interviews lasted up to an hour and were conducted

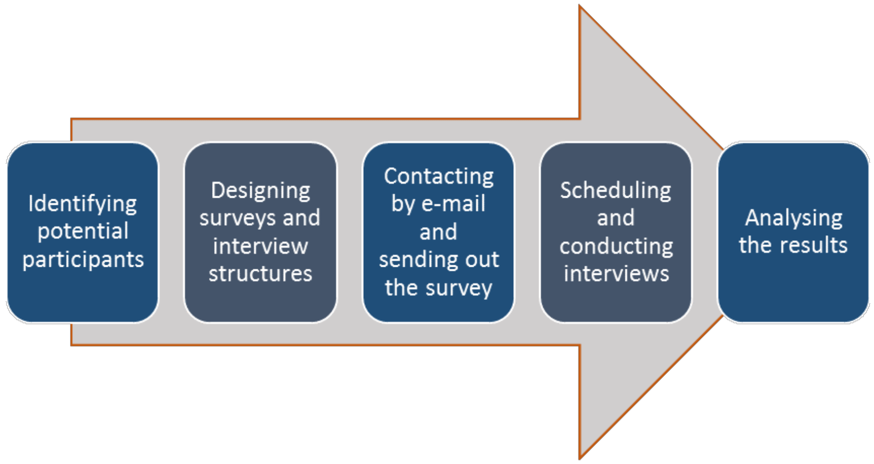

Figure 2.1. Main stages of the study

nationwide across a wide spectrum of stakeholders, which is among the first of its kind to the best of our knowledge. The surveys were administered primarily to further validate and quantify the conclusions from the interviews. This is because the transportation industry is currently going through a constant state of flux. Thus, there is a significant amount of uncertainty in how the CAV environment will unfold. Therefore, only a mechanism that encourages, the exploration of new ideas during the interview process can capture the multi-dimensional aspect of this phenomena. The multi-step process from planning to analysis of results has been broadly summarized in Figure 2.1, and is followed by a detailed step by step description of each stage.

2.3.1 Identifying potential participants

Preliminary internet research was carried out to prepare a list of points of contact from universities, DOTs, OEMs and other organizations working in the CAV domain. To guide this list's development, the United States was segmented into 10 regions. At least two individuals were interviewed from each region. This ensured that various regional opinions were accounted for, since the state of development of CAVs differs by region.

2.3.2 Designing Interview and surveys

Next, a literature review was carried out to identify gaps in past research and arrive at potential topics of interest. The interview questions were based on the following two major themes identified by the literature review: organization-related and CAV-related. While the former sought to understand the impact of each organization, the latter aimed to understand every organization's perspective on CAVs. The structure of the interviews was as follows:

1. Organization related
   (a) Objectives
   (b) Opportunities
   (c) Threats/Challenges
2. CAV related
   (a) Views on the future of CAVs
   (b) Obstacles in adoption
   (c) Challenges due to lack of standardization
   (d) Maturity of technologies
   (e) Required levels of maintenance of infrastructure

Interviews were semi-structured, as they were customized for different types of stakeholders. Moreover, the questions were subjective to allow the interviewee to answer from a personal perspective. The survey was principally designed to perform a supporting role to the interviews. A survey previously conducted by Foley and Larder LLP [17] looks at important themes in the CAV landscape, but is limited in its scope and depth because the respondents are mainly business executives from OEMs, technology and financial firms. We believe it is very critical for policymakers and other stakeholders to have a very clear understanding of each stakeholder's opinion in the CAV environment to take optimal decisions. Therefore, we have expanded upon Foley and Larder's work to include technical experts and thought leaders from private, public and university domains. The main themes identified for the survey were evolution of CAVs, attractiveness of different SAE levels, and competition and area of focus in the CAV domain. Some of these concepts are captured in the Foley and Larder survey [17]. Therefore, our study employs 9 questions from Foley and Larder [17] that are relevant to the ideas we are exploring. The study expands upon that of Foley and Larder by introducing 6 additional questions relevant to the explored ideas. This resulted in a final survey containing 15 total questions being distributed to all respondents.

2.3.3 Contacting by e-mail and sending out the survey

Once the interviews and surveys were designed, the next step was to contact potential participants. A formal e-mail introducing our research group and the objective of our study was sent out to the previously-prepared list of contacts. The survey was prepared using Qualtrics and was also sent out in this e-mail along with the request for a phone interview.

2.3.4 Scheduling and conducting interviews

A total of 28 responses were obtained from the e-mails sent out in the previous step. For all responders, phone interviews were scheduled and permission to record the interview for transcribing purposes was sought. A list of interview questions was also sent out beforehand. This helped the interviewees pace their responses as per the availability of time.

2.3.5 Analyzing the results

At this stage, the raw data at hand was comprised of responses from the survey in a csv (comma separated value) format and audio files of the recorded interviews. Information from the recordings was then summarized in a document for easy reference. Thereafter, the data from survey and interviews was assessed to detect important trends and patterns. Based on the trends thus identified, recommendations for different stakeholders were developed. These results and recommendations have been discussed in subsequent sections.

2.4 Results

2.4.1 Stakeholder Analysis

This section provides a stakeholder analysis of the players in the transportation industry. Figure 2.2 details the different stakeholders the interviews covered. We conducted 28 interviews. These involved a total 31 individuals due to the occurrence of several multiple-person interviews. Due to the highly competitive nature of the industry and the inherent criticality of the transition, the response rate between different stakeholders varied significantly. For example, even though some of the private stakeholders, especially OEMs and application developers, are among the most impacted in the transition, they had a low response rate. Conversely, the state DOTs were eager to discuss their views of a CAV future and plans to ready themselves. To elaborate on the term transition it encompasses the changes in the transportation industry that are ushered in due to CAVs. Below is an analysis of each stakeholder.

Federal agencies

Federal agencies like USDOT, NHTSA, FHWA, and ITS JPO are keen on introducing CAVs on the roadways. A study done by NHTSA found that 94% of road

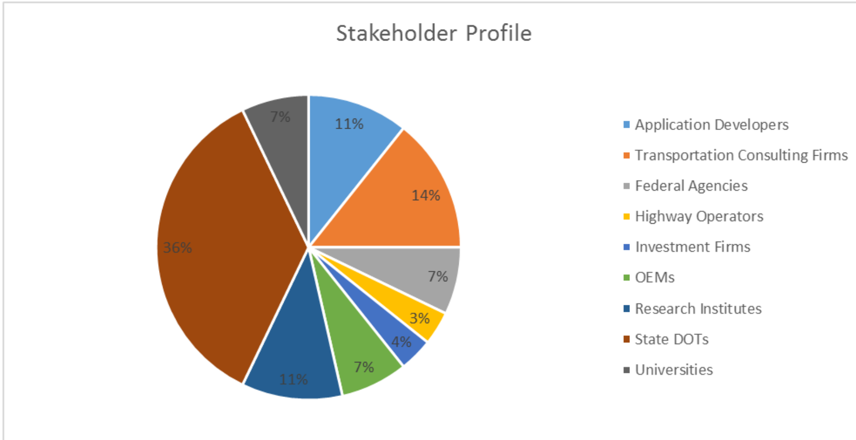

Figure 2.2. Profile of Interviewed Stakeholders

accidents are attributable, at least in part, to human error (NHTSA, 2008). These agencies believe this can error avoided by the introduction of AVs. In its first ever guidance on AVs, NHTSA in 2016 discussed guidance for AV performance, model state policy, and regulatory tools (NHTSA, 2016). Also, it embraced 6 levels of SAE automation in its guidance. In 2015, FHWA released the guidance for V2I technology within a connected environment (FHWA, 2015). Though this guidance is not mandatory, it intends to support the transition when taken up by public agencies. ITS JPO has floated multiple initiatives to push forward an intelligent transportation system environment. It conducted a connected vehicle safety study between 2011 to 2013 to assess the safety impacts of CV applications on transit and light weight vehicles. ITS JPO has also funded a 100 million USD program to implement CV applications, which has already begun in three cities.

State DOTs

The state DOTs are trying to build capabilities in the agency to adjust to a fast-changing transportation landscape. Many of them are building roadmaps to make sure that they are not caught by surprise. The leading DOTs are trying to focus on research and implementation of various CV applications. Wyoming, New York and

Florida are part of the CV pilot where they are testing freight, safety, and toll related CV applications. Various states have implemented different levels of regulations to manage AVs on their roads. States like California and Arizona have openly embraced AVs on their roads, while other states have restricted access. Other initiatives, such as pooled fund studies, have been very useful for state DOTs. This is because pooled fund studies assist the implementation of solutions to problems faced by states and, at the same time, can lean on the experience of the more proactive states. State DOTs are involved in various challenges, like the signal timing challenge, which will further push their involvement in the area.

OEMs

All OEMS are keenly observing this transition, as it has the potential to shift the balance from vehicle ownership to transportation-as-a-service. They will need to be very proactive to make sure that they ride this wave or take the risk of being left behind by the multiple new players in the market. The traditional automakers were initially slow to react, but, with more technology firms coming into the space, all the major firms have ramped up the focus on AVs and have communicated very optimistic time lines for launching their automated vehicles. They are aware of the challenge due to the transition from retail format to transportation-as-a-service and are evaluating business models that will help achieve this. They are planning to collaborate with ride hailing apps, which have had very good success in this area.

Highway Operators

Highway operators are excited about the implementation of the new CAV technologies. They are hoping that new technologies can provide drivers with more information to make better decisions. They believe applications such as curb speed warning, intersection entry assist, pedestrian connected crosswalk, signal timing control based on flow can improve safety and mobility, which are their two prime focus areas.

Transportation consulting firms

The consulting firms are in a unique position. Until now, they were advising their clients in the public and private sectors regarding what to do in terms of transportation planning and design. With the advent of the CAVs, they find themselves in a spot where they need to learn quickly before they can guide. Consulting firms are ramping up their CAV consulting arms with multi-disciplinary teams to tackle the problems from various angles.

Application developers

Applications developers see substantial opportunities in the space opening up. The number of CAV applications has increased tremendously in the past few years. CV applications have grown significantly in the areas of safety, mobility, environmental, and road weather space. In the AV space, multiple applications, including adaptive cruise control, lane keep assist, traffic jam assist, forward collision warning, parking assist, and automatic emergency braking, are being deployed. Furthermore, more sophisticated applications are being developed.

Investment firms

Investment firms recognize the CAV disruption as a once in a century kind of an event. They opine that the biggest investment returns occur when a legacy industry is subjected to disruption. For automakers, this disruption is driven by OEMS and autonomous vehicles. Wealth is created when dynasties transition or dynasties fall, both of which is happening in the transportation industry. Finding the best start up can be a big challenge. For example, even if an investment firm knows that LIDAR is the next big thing that goes into AVs, there are many companies working on LIDAR-related ventures. One needs to obtain detailed information on all startups to make the best decision regarding which one to invest in.

Universities and Research Institutes

Universities and research institutes are playing a key role in the development of CAV technologies. They are not only working on theoretical problems, but are also collaborating with state agencies and private institutions to study the impact of various state-of-art technologies. Based on these studies, universities and research institutes provide recommendations on how to improve CAV technologies. Some of the research universities, such as the University of Michigan, have helped set up testing grounds for new CAV applications

2.4.2 Interviews

In this section, we discuss the results of the interviews in two parts: organization related interview results (Table 1)and CAV related interview results. The organization related interview results are tabulated to provide a comparative understanding of stakeholders across different issues.

Organization-Related Interview Results

In this section, we discuss the various objectives, opportunities, threats, and challenges each of the players face in the CAV domain.

1. Federal Agencies

   Objectives: Create a framework for seamless integration of CAVs from a policy perspective.

Opportunities: Mandating V2V technology will make the road systems safer and more efficient through widespread information sharing and movement optimization.

Threats/Challenges: A national level problem relating to CAV technology is the lack of comprehensive regulations, which effects stakeholder actions and slows them. The interoperability of connected vehicles across state boundaries is in question due to a lack of regulations standardizing the technology.The federal government has made a significant investment into DSRC technology. If 5G turns out to be a better option, there might be legacy issues.

2. State Agencies

Objectives: Focus is on becoming more aware of CAVs and the impact they will have on transportation planning.

Opportunities: CAVs can improve deceleration profiles at signals, transit schedule reliability, physical road conditions and mobility under poor visibility with CV applications. From a safety perspective, state agencies see potential in the technology to improve driver awareness. It can reduce driver fatalities to zero if properly implemented. DMVs can be restructured if AVs become common. Less people will require licenses, making DMVs easier to operate.

Threats/Challenges: In the future, AVs will necessitate new transportation planning. For example, instead of commuting in their own vehicles, a portion of the population will commute in AVs. The logistics of this process are very complex and need to be determined by DOTs across the nation. For instance, it is unknown whether AVs will decrease the demand of urban parking, transit, or vehicles in general.

CAV industry is moving rapidly, and it is hard for DOTs to stay abreast of what different states are doing, what is going on in different countries, what each company is saying in terms of their timeline and the changes in technology like Lidar, camera systems etc.

3. OEMs

   Objectives: Maintain market position by investing in CAV technologies. Continuous testing of their technologies will improve their efficiency and safety levels.

   Opportunities: There are new business opportunities. For example, transportation-as-a-service is exciting for the OEMs.

   Threats/Challenges: Many new players are entering the industry. Technology companies, which are not traditional auto manufacturers, are a potential threat to established OEMs.

4. Highway Operators

   Objectives: Interested in the implementation of CV applications as well as how CAV deployment will impact their operations.

   Opportunities: Access to CV data for improved traffic operations.

   Expecting to see benefits to show early. Use new technology to fill in the gaps of the current technology.

   Threats/Challenges: Integration of new technology with the old technology. Lots of the new technology requires high saturation rates.

5. Application Developers

   Objectives: In the short term, they will focus on revenue generation by providing engineering services to big organizations. Additionally, they will focus on building intellectual property with the suite of development tools and applications from both the vehicle and infrastructure side.

   Opportunities: Focusing on optimization of traffic flow and collision avoidance will drive a lot of business towards DSRC and 5G technology in the CV space.

   Threats/Challenges: The government announced two years ago that they were going to mandate connected vehicle technology in automobiles by 2020.

That mandate still has not occurred, and it is not clear that it ever will. So, that uncertainty creates a threat all by itself. People are poised to move forward, but do not necessarily want to without that mandate occurring.

6. Research Institutes and Universities

   Objectives: Identifying new challenges with the oncoming revolution and find solutions. Multidisciplinary expertise is available to tackle intricate, cutting-edge problems

   Opportunities: Multidisciplinary expertise is available to tackle intricate, cutting-edge problems.

   Threats/Challenges: Recommendations and solutions can get outdated due to the fast-paced nature of the CAV landscape.

7. Transportation Consulting Firms

   Objectives: Helping clients become educated about the technology and helping them to figure out what they need to do from planning, policy, and engineering perspectives.

   Their primary focus is on supporting public agencies. They also are looking to play the role of a liaison between DOTs and technology companies in implementing CAV solutions.

   Opportunities: The biggest opportunity will be to change the mindset of how to do their planning. They will need to transform into a more agile and adaptive process, while constantly monitoring the changes in real time and adapting their interpretation and investment ideas.

   Threats/Challenges: A huge threat is that they will need to restructure their teams to include more ITS officials to work with CAVs.

   They will need to shift from a traditional civil engineering firm to an interdisciplinary organization. They are growing their emerging technologies' practice to bring people with ECE and CS backgrounds into the fold for the 21st century.

Most of their clients are not even hiring them yet for CAV related projects because they do not know what they will need in this space. The more progressive clients are starting to talk about roadmaps required regarding CAVs.

8. Investment Firms

   Objectives: They are looking to enter the supply chain and would like to position themselves for higher level vehicles. They believe highly autonomous vehicles will have a disruptive impact on the market.

   They are focusing on developing revenues and relationships now so that they are well positioned for the medium term.

   Opportunities: There is significant interest from big corporations in terms of finding the right businesses to fund. The investment firms will be the connection between the big corporations and CAV technology startups.

   Threats/Challenges: Lots of investment firms are specifically focused on autonomy and, because of that, they are very open to risk. This is especially true when they are investing in currently unprofitable startup companies. The time delay to market will put a strain on these investment firms.

CAV-Related Interview Results

In discussion with the respondents, there are some key concepts that arose of critical importance.

1. The interplay of connectivity and autonomy

   The views of industry and state agency figures are divided on the potential interplay between connectivity and autonomy. Industry figures believe connectivity and autonomy are mutually exclusive. In their opinion, it is hard to maintain connectivity through all scenarios of driving. When connectivity was proposed, then machine learning and computer vision were nascent technologies. These technologies have since developed by leaps and bounds. Additionally, the proposed rulemaking [73] timeline is uncertain, which could result in very few OEMs setting up connected devices in their vehicles. In such an unregulated environment, CV penetration will be insufficient for connectivity to be effective. Due to the above reasons, OEMs are not relying on connectivity for their autonomous systems. Although corner cases can be supplemented by connectivity. For example, the trajectory can be more reliably predicted if the vehicles can receive the GPS position of the vehicles ahead of them through CV applications. Nevertheless, automakers are not currently relying on these kinds of applications to improve vehicle performance.

The state agencies, on the other hand, support connected automation. They believe that connectivity integrated with automation, can improve vehicles' capabilities situational awareness and make them safer. This will be superior to an exclusively autonomous vehicle. Transportation consultants opine that connectivity is only inevitable and will make autonomous vehicles more functional and safer. Despite a support for connectivity along with automation from most stakeholders, automakers are building functional autonomous cars without connectivity. This is due to advanced automated systems and uncertainty on mandating connectivity in vehicles.

2. Evolution of CV

   Most of the respondents from state agencies have stated that the advancements in CVs are already underway. CV applications are in various stages of design and testing to improve vehicle safety and mobility. Many cars have embedded cellular and Wi-Fi technology, which is being used for transmitting traffic and software updates. Their evolution will depend on the public sector, as rulemaking mandating their standardization and implementation would rapidly expedite CV technology's introduction rate. One of the participants had an optimistic view that connected devices will be in most new vehicles produced by 2020. The consensus view is of measured optimism for the growth of CVs, given the uncertainty on the proposed rulemaking. In fact, several of those interviewed said that the Trump administration seems to be reluctant to issue a federal mandate for connectivity.

3. Evolution of AV

Many industry respondents observed that the evolution of AVs will bifurcate into two different directions. One direction will be the deployment of semi-autonomous Advanced Driver Assistance Systems (ADAS) in vehicles via the traditional retail market route. The other direction will be the deployment of highly autonomous vehicles via transportation-as-a-service concept. These vehicles will be owned and operated by new age taxi applications or by OEMs themselves.

We are on the cusp of a major change in the traditional supply chain system in the automotive industry if the above views materialize. The biggest motivator for pushing for this change is the lack of a profitable business model for the highly autonomous vehicles (HAVs). Due to the multiple sensors that the HAVs will be equipped with, their market price will be out of range for a large proportion of consumers. One way OEMs believe will reduce these costs and give them greater control over the vehicles is to introduce HAVs via car sharing services. Under the transportation-as-a-service idea, the vehicles will not be owned by individuals, but rather will consume transportation service provided by a service provider. As a part of this plan, the HAVs, which will go by the name of Robo-Taxis, will operate in geo-fenced cities. Geo fencing is the defining of geographic boundaries using GPS systems. The customer will consume the services and the service provider will manage the fleet. Interestingly, due to significant difference in the business models and technologies for semi-autonomous vehicles and HAVs, the interactions within the OEMs, between these two departments does not seem to be strong.

4. Infrastructure requirements

   One of the concepts explored was whether industry participants should build vehicles based on current roadway conditions or should DOTs improve the road infrastructure. Some industry participants believe that they need to make AV technology work on road conditions that exist as of today. However, other industry participants believe it is not an either-or question. They believe it is in the state's best interest to provide good quality roads, signs, and road markings for the vehicles that operate on them. At the same time, it is the technology's responsibility to be able to safely operate on the current state of road infrastructure. The state can choose to not maintain the infrastructure as well as it is mandated to, but this could cost lives and hurt developments of CAVs in the state.

   Although the state agencies recognize the need for improvement, they maintain that it will be a big challenge to make sweeping changes to their massive roadway networks. From a practical standpoint, they opine that the vehicles should be able to perform reliably on the existing roadway infrastructure. Some minor changes can be done by the DOTs, but if there is a need to overhaul the entire infrastructure, that will not be a feasible option. The research institutes believe that state agencies should explore public–private partnership options to fund the infrastructure improvements.

5. DSRC vs 5G

   While rulemaking is currently in the process of being instituted to mandate DSRC, proponents of a competing technology, 5G, are challenging the legitimacy of such a requirement. The FCC wants to reserve space for 5G in the 5.9 GHz spectrum to perform vehicle safety functions similar to those performed by DSRC, while also serving an entertainment purpose through expanding internet access [36]. It must be noted that the FCC currently has regulations on DSRC technology, specifying licensing and service rules. 5G is "still very much in the draft stages" [21]. Standards defining details even as simple as what the term "5G" means are being drafted [21].

Despite a lack of current development, 5G will eventually be able to "compete with DSRC in terms of latency, security and guaranteed throughput", per Dominique Bonte, an ABI Research vice president [22]. The key advantage of 5G technology over DSRC is that it will run off existing infrastructure: current wireless networks. 5G technology upgrades will still need to be made at cellular stations, but the infrastructure is present to support them. On the other hand, DSRC's adoption will require taxpayers to fund a national introduction of DSRC roadside stations. 5G can also be used for entertainment purposes, which will enable it to be a unifying connectivity technology for cars through integrating safety and entertainment features [22].

6. Need for standardization of connected vehicles

   The biggest challenge faced by CVs will be communication protocols. Standardization of communication to ensure interoperability is a challenge. Therefore, it will be necessary to achieve this. State DOTs mentioned that there are no directions from federal levels of CAV standards. This is going to slow down the process. The downside of having standardization is the potential for the people writing regulations to not have an adequate understanding of CAV technology and consequently box the industry into a corner. The state agencies can get monetarily affected if there are sweeping changes required to adhere to the required standards.

7. Need for standardization of Autonomous vehicles

   Currently, there is a lack of standardization. Different companies are looking at different technologies and there is uncertainty regarding what standards are appropriate. As a result, most major firms are developing their own capabilities. For now, it is acceptable not to have standardization because the solution space needs to be analyzed for the best solution.

2.4.3 Surveys

The surveys were the second part of the two-step analysis conducted, to validate some of the conjectures drawn from the interviews. Results from the survey are presented below, grouped into five themes. Questions with superscript as 1 allowed selection of multiple options as response and questions with superscript as 2 are employed from Foley and Larder study [17].

Path to CAV Development

This theme intended to understand how different stakeholders expect CAV technology to develop. In general, the path to CAV development is expected to be evolutionary Figure 2.3a and Figure 2.3b While this is the widely held opinion for CVs, a significant proportion of the respondents do expect AV development to be revolutionary.

Figure 2.3 discusses the obstacles to CAV growth. Maturity of technology is the most important concern for AVs. Regulatory and safety concerns are also significant for AVs. In addition, price, privacy, and regulatory roadblocks are expected to be major obstacles to the growth of CVs. The privacy issue is in line with the intuition that it is connectivity which creates privacy concerns, not simple automation.

Figure 2.3 shows the challenges perceived by organizations in CAV development. In the wake of auto manufacturers promising to have CAVs on the roads by early 2020 [23], most of the respondents acknowledge that technology not being ready for deployment is the biggest challenge for them. The next big issue is infrastructure not being of acceptable quality.

Attractiveness of different SAE levels

This portion sought to recognize the expected short-term appeal of different SAE levels of automation. . Figure 2.7 shows that SAE level 4 is expected to be the most

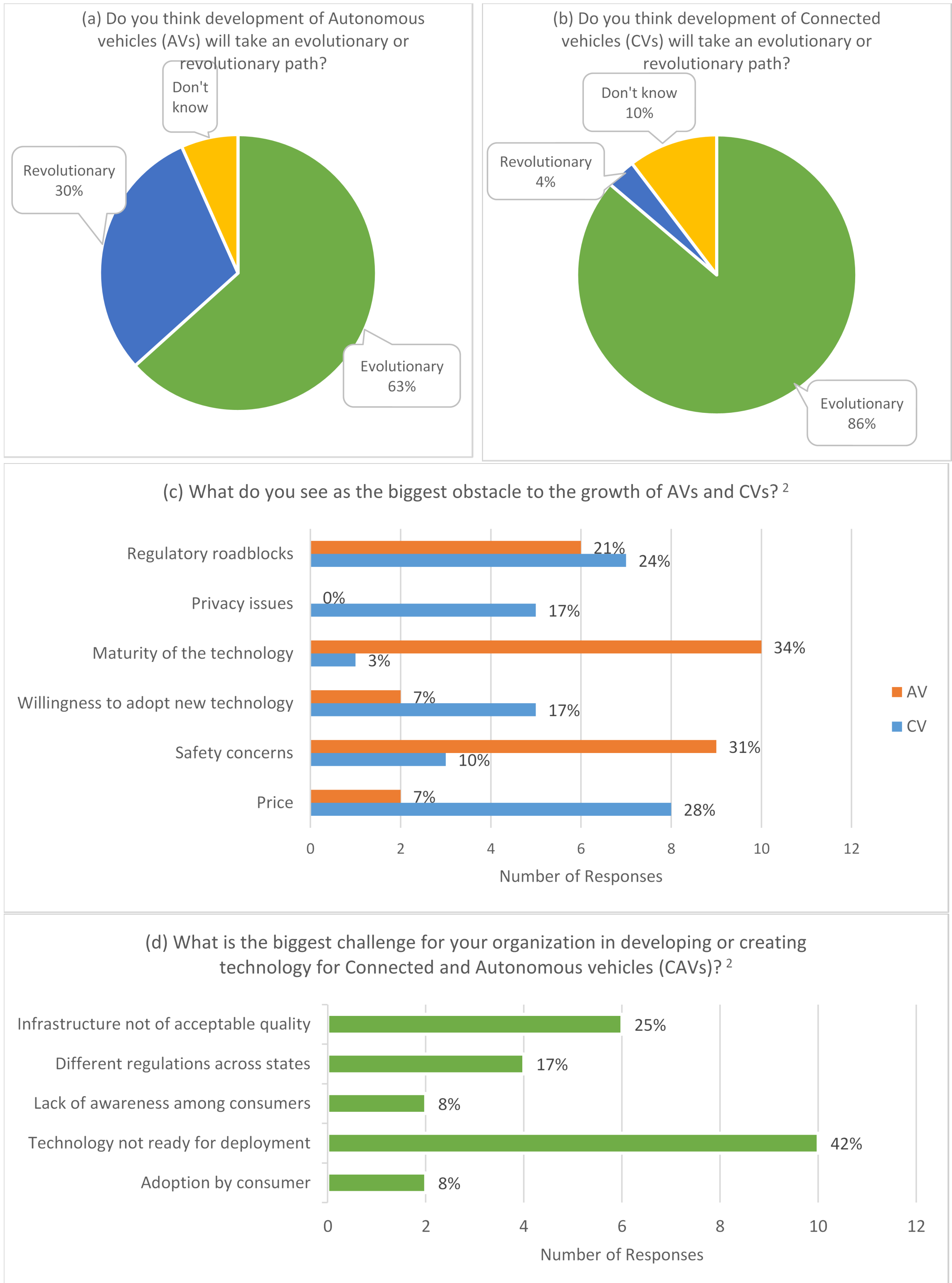

Figure 2.3. Path of CAV development

attractive to the consumers. This aligns with the observation that most organizations in the sample (around 70%) are focused on automation levels at or above SAE level 4. SAE levels 2 and 5 are also being focused upon by a significant proportion of the respondents. The question in Figure 4a allowed selection of multiple options as a response.

The Expected Future of AVs

This theme explored the stakeholders' opinions on some key questions related to an autonomous future (Figure 2.4). Figure 2.4a caters to the dependence of automation on connectivity. Interestingly, the percentage of respondents who expect automation to be effective without connectivity is significantly higher (25%) than those who do not (7%). Figure 2.4b investigates the penetration of AVs in terms of expected sales, which revealed nothing concrete. In Figure 2.4c, the respondents expect all legal issues to be critical. Nevertheless, data management, attributing liability in an accident and cyber-attacks seem to be more significant as compared to others.

Organization Specific

Organization specific questions intended to understand what organizations are focusing on to prepare themselves for a CAV future, as shown in Figure 2.5a, 2.5b, 2.5c. While almost half the respondents are focused on AV development, the percentage focused on developing CVs is at least half.

Competition

This theme aimed at capturing the dynamics between different stakeholders in terms of their competitors and perceived threats. Figure 2.6a shows competition is high amongst the stakeholders, especially technology companies. Furthermore, Figure

2.6b shows that around 80% of the respondents expect the new entrants to disrupt the market, thereby increasing competition.

A summary of the survey results was discussed above. The next section explores these results in detail to identify important trends and inferences.

2.4.4 Analysis

Interviews

A complete analysis of the stakeholder interviews was conducted. The various stakeholders involved are excited about their participation in this transition, which could be the new face of transportation as we know it. However, the incentive for each stakeholders is different. The private sector aims to maintain its market share

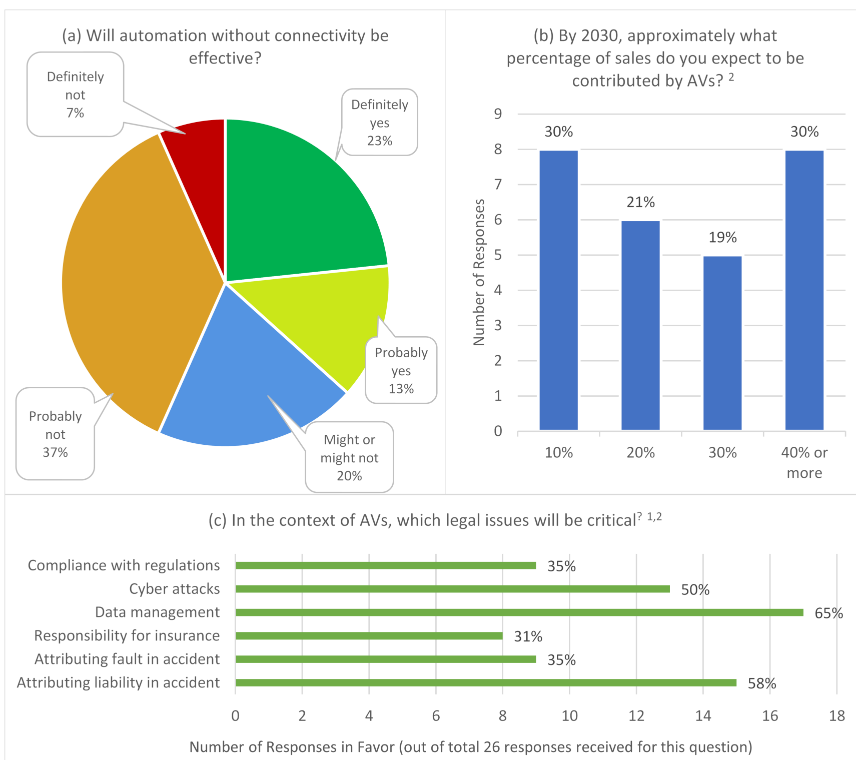

Figure 2.4. Expected future of AVs

and remain relevant to customers. The public sector's focus is to improve vehicle mobility and safety. In spite of the differences in objectives, both sectors are extremely interested in making this a success.

The challenges that the private sector faces are uncertainty in the choice of technology for CVs, the time line for mandating standards for CVs, the evolution of

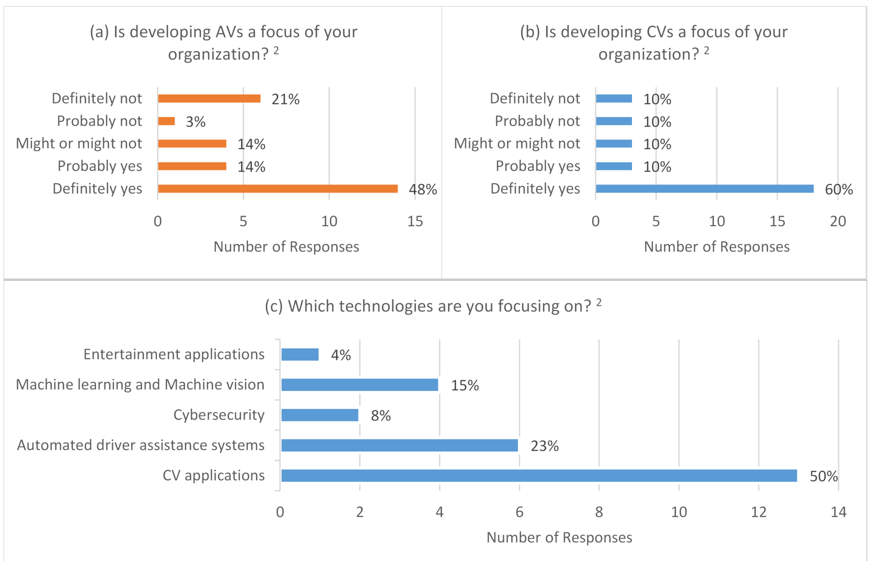

Figure 2.5. Organization specific

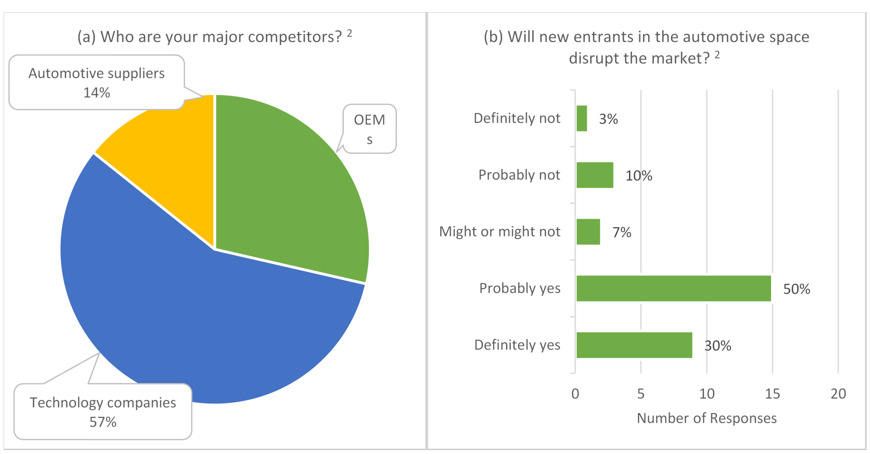

Figure 2.6. Competition

industry structure for AVs, and competition from new entrants. On the other hand, the challenge for the public sector is to understand the technology to pave the right path for the industry. Some of the challenges that the stakeholders face are due to the actions of the other players and hence can be solved by stronger partnerships. Currently, the partnerships between the stakeholders are mainly limited to supply chain alliances.

One of the main reasons for private players to refrain from collaborating is the threat of competition [24]. Nevertheless, there needs to be a more concerted effort to have strategic partnerships. Collaboration will improve the effectiveness of their efforts significantly. On the other hand state agencies have been more successful in building partnerships to enhance the CV efforts. There are multiple coalitions, pooled fund studies, and pilot programs which endeavor to assemble the various players in a collaborative venture [25] - [27].

The lack of clarity about the CAV future and each of the stakeholder's role in it is very apparent among all the players. This is understandable, as this crossover to a new paradigm is momentous. There is a clear trend of isolated efforts by the players to maximize their individual performance.

The evolution of the AV space has taken an unexpected turn recently. The AV industry has made good progress in building the technology to achieve automation.

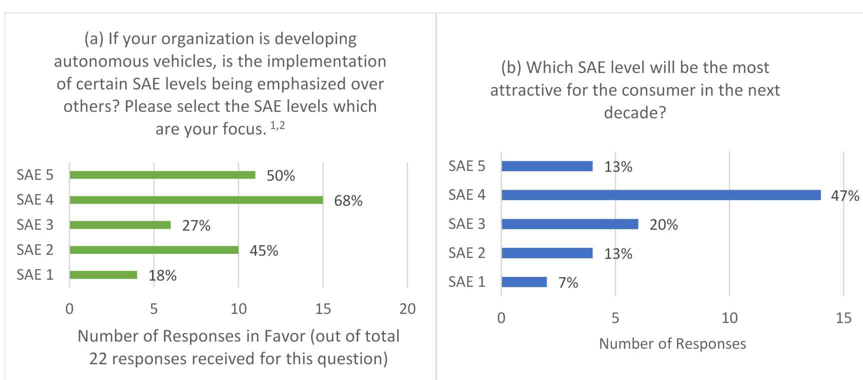

Figure 2.7. Attractiveness of different SAE levels

But there has been as much clarity on the business model component, especially for the highly automated vehicles (HAVs). HAVs were initially thought to be introduced through retail. Due to their high price, the retail market will be modest at best. Recently, in the light of the success of taxi hailing services, the business model for HAVs has been shifted to a Robo-taxi model [27]. This means they are expected to enter the market via transportation-as-a-service model. Prices of the transportation service will be minimized by high vehicle utilization and no driver overhead. These will mainly be categorized as SAE 4 level vehicles. The deployment of these robo-taxis will be in geo-fenced cities. In terms of managing these vehicles, the OEMs will either deploy their own fleet of vehicles or partner with the ride hailing companies like Uber and Lyft. The operations of these vehicles will be monitored by the OEMs to ensure that they are functioning in their Operational Design Domain (ODD).

There are divergent views held by the various stakeholders on the need for connectivity in autonomous cars, but some opinions take a more moderate approach. AV technology was dependent on connectivity when it was in its infancy. Despite this, industry participants believe the way forward for AVs is to be completely autonomous. The private sector does not want to over-depend on connectivity, as there is no concrete time line on the DSRC mandate and other V2I implementations. Therefore, to have complete control on the performance of AVs, they prefer a design that only requires AV technology to function. On the other hand, state agencies believe that connectivity is imperative for autonomous vehicles. According to them, AV performance without connectivity will be suboptimal. Hence, federal and state agencies have invested significant resources to develop V2V and V2I communication and will want to see this investment result in some useful applications.

The views on the role of state agencies in infrastructure maintenance and improvement to suit AV needs are divergent. The state agencies' biggest challenge to cooperate in this dimension is the lack of monetary resources. Any change needed for implementation at the city level or greater will put a strain on the budget of the DOTs. In fact, state DOTs may need assistance from the federal level to implement any sweeping changes. The OEMs understand this situation. They do not rely on any significant infrastructure improvements to facilitate AV performance. However, they certainly expect that states will maintain their infrastructure up to certain standards, such as preserving lane markings. Nevertheless, OEMs will need to make sure AVs can navigate under non-complaint conditions, as they will surely be encountered.

The public sector is the main actor pushing the advancements in CV technology. There are multi-directional efforts in research, design, testing and deployment of CV applications. Many state DOTs have established their own CV research and development programs to better implement CV applications for their unique requirements. There are many concerted efforts as well, wherein multiple states are working together on problems that collectively concern them [28]. In addition, there are pilot programs and other national level programs initiated by the USDOT. Although these efforts are in the right direction, they will still need to be streamlined at some point at the federal level to accelerate the implementation of the work labored by different entities.

Surveys

From the survey results presented above, the following trends in stakeholders' views can be inferred. These have been discussed in detail below:

1. Immaturity of Autonomous Vehicle Technology

   Concerns regarding the maturity of the technology are noticeable. Most respondents perceive maturity of technology and safety concerns to be the biggest obstacles to the growth of AVs(Figure 2.3c). Along similar lines, most respondents chose "Technology not being ready for deployment" as their biggest challenge in developing CAVs (Figure 2.3d). Furthermore only 13% respondents think that SAE level 5 will be the most attractive to consumers in the next decade, as opposed to 47% in the favor of SAE level 4 (Figure 2.7b). In fact, the same can also be loosely inferred from the responses in Figure 2.4b, where only 30%

respondents indicated AVs will contribute more than 40% sales in the coming decade. Thus, autonomous vehicle technology is not mature enough for deployment, which jeopardizes their launch by the early 2020s as promised by most car manufacturers [23].

2. Attractiveness of SAE level 4

   SAE level 4 is expected to be the most attractive to consumers in the next decade (Figure 2.7). Consequently, most of the surveyed organizations are focused on implementing SAE level 4 Figure 2.7. SAE level 4 corresponds to the level of automation where the vehicle can drive itself completely. If it encounters any unprecedented situation, it seeks human intervention. SAE level 3 lacks this aspect of handling the situation if the requested human intervention is delayed. SAE level 5, on the other hand, corresponds to complete automation wherein the vehicle does not need human interference at all [29], [30]. Consistent with the previous conclusion, a lack of maturity on the technology side undermines the short-term feasibility of SAE level 5. In contrast, the attractiveness of SAE level 3 is hampered by its instability when dealing with unexpected road conditions [31]. On the whole, it seems reasonable to expect high attractiveness of SAE level 4 autonomous vehicles in the coming decade.

3. Evolutionary Path of Development of CAVs

   The path to CAV development is expected to be evolutionary (Figure 2.3a and Figure 2.3b, i.e. CAVs are likely to grow in a gradual step-by-step fashion over the coming decade. The notion of evolutionary change is opposite to the idea of revolutionary change, in that the latter implies sudden and forced change within a short stipulated time period. This can also be inferred from Figure 2.4, which shows that the contribution of AVs in sales is not expected to be high in the next decade, thereby indicating that AVs will gradually penetrate the market.

4. Transportation-as-a-service There is growing consensus that the evolution of autonomous vehicles will take two paths. One path features lower level SAE vehicles being introduced in the traditional retail fashion. For HAVs, the path will be different, as OEMs and transportation service providers will deploy level 4 and 5 vehicles via transportation-as-a-service. The evolution of CVs will depend on the implementation of the proposed rulemaking. There are other components, such as need for standardization of applications, development of the technology, and collaborative research on V2V and V2I applications, that will impact the evolution. The business models necessary to make SAE 4 vehicles viable are still debatable in the industry. One of the advantages of SAE level 4 will be the removal of the human driver from the equation, reducing the operating cost of vehicles. SAE level 4 vehicles will not come out in retail format, as the market for them at current prices will be lackluster. Therefore, they will be deployed as robo-taxis for transportation services. The deployment of robo-taxis will be done city-wise. Since the SAE level 4 vehicles operate only in their ODD, they will be deployed in geo-fenced areas.

5. Disruption of Automotive Industry

   It can be inferred from the survey responses that the emergence of CAV technology is almost certain to disrupt the existing automotive industry. 80% of the responses in Figure 2.6 consider it likely. In fact, owing to this development, technology companies are expected to emerge as strong competitors in the market Figure 2.6. This can also be seen from organization-specific data in Figure 2.2, where a significant number of companies focused on technological applications seemed to have ventured into the market.

2.4.5 Recommendations

From our analysis of the interviews and surveys conducted with various stakeholders, there were a few themes that stood out. Based on the discussions and inputs from the interviews we present recommendations to increase momentum towards a CAV future.

OEMs need to focus on testing the AV technologies to make sure they perform in all scenarios. This entails experimenting with several variables: road and weather conditions, traffic states, time of day, and more. Testing is of prime importance to ensure the safety of the passengers and other traffic. Also, to ensure wide acceptance of AVs, OEMs will need to convince customers of the safety and mobility benefits. Additionally, OEMS should partner with state agencies to build collaborative efforts to streamline AV development. Moreover, OEMs will need to change how they operate to compete with new players like Tesla. To accomplish this, they should think of themselves as a transportation service provider instead of a automaker [32] - [33]. They will further need to collaborate with the ride hailing companies.

From the overwhelming consensus of the interviews conducted, state agencies should prepare for an evolutionary CV development path. The deployment of CVs is going to take a while. Since the technology and standards will evolve significantly during deployment, the state agencies interested in CVs should focus on research and development instead of deployment for now. State agencies should wait for the DSRC 5.9 legislation to pass before deploying CV technology. They should collaborate with other states to be a part of CV research, thereby minimizing the research investment required. Given DSRC's established nature, it should be each state DOT's primary area of work in the present and near future. They should also stay informed with 5G developments, but DSRC should be the agencies' focus for CV infrastructure. To capture the advantages of CAV technology, state agencies should identify key weaknesses in their road systems and determine connected vehicle applications that can rectify the issues. State agencies should also build ties with research universities to get assistance in learning about CAVs through research projects. Proper management of the technology will require expertise in knowledge outside civil engineering. Therefore, state agencies need to hire experts in ECE, systems engineering, and systems operations to operate CV technology. Application developers who are focusing on the CV space should be flexible with regards to communication systems. Currently, DSRC is preferred by most stakeholders, but there are implementations of 5G in Europe. 5G technology may become dominant as an alternative technology for CV applications. In the AV space, the technology developers will need to focus on achieving the desired functionality at lower costs to be successful. Also, untapped potential exists in the opportunity to provide AV platforms that are interoperable.

Firms invested in CAV technologies will be required to balance their portfolio to account for uncertainties. The uncertainties can be due to superior new technologies or from delays in the deployment of CAVs on road. In these scenarios, they will be impacted by reduced revenue streams and lower value for their investments. To alleviate these concerns, they should provide support to the companies invested in. The nature of support can include providing training for how to scale operations and networking with different players in the transportation industry to improve their product. To have an edge, they need to build strong ties with leading research teams to stay abreast of the latest technological developments and understand how that impacts their current investment.

Research institutes and universities must adopt an interdisciplinary approach to solve problems in the CAV space. Collaboration among university disciplines is required to perform meaningful research. Consulting firms that are looking to build expertise in the CAV space will face a steep learning curve attributed to the ever-changing CAV landscape. The expertise of their teams working on CAV related projects will need to include other disciplines as well, which will help provide a multidimensional understanding of the issues.

2.4.6 Conclusions

The opinion on the roadmap for both AVs and CVs is divided between being revolutionary and evolutionary outlooks. This is because there are many roadblocks in front of CAVs that presently lack a clear solution. The respondents' outlooks are consequently split on this point.

Among the main obstacles impacting large scale deployment for autonomous vehicles are the public perceptions of the safety and cost entailed by AV ownership. Standardization in the AV space is not needed right now, as the best applications are still being developed. Hence, there needs to be freedom for innovations. Standardization in CV applications, on the other hand, is required. This is because interoperability is of key importance in CVs. The maturity of CV technology is, to a large extent, acceptable across all participants. They believe it is only a matter of time before glitches are removed. However, the real challenge with AVs is to take care of potentially lethal glitches, such as poor infrastructure resulting in crashes. The AV industry is not relying on state agencies to improve infrastructure conditions. Furthermore, state agencies also agree that changes and improvements in all critical areas will require significant funds and time.

Connectivity will be an inevitable consequence of the need for more information in a vehicle. However, some industry players believe connectivity will not play an integral part in improving vehicle mobility and safety. On the contrary, state agencies believe connectivity will play a role in enhancing the mobility and safety of vehicles. The partnerships across CAV stakeholders are not very strong, one of the reasons is because automakers and other private players did not need to collaborate with public agencies to such a significant extent until now. A strong partnership between the private firms and public agencies can guide the roadmap of the evolution of CAVs in a more efficient way, but this will require significant efforts from all parties involved.

3. MOBILITY IMPACTS OF AUTONOMOUS VEHICLE SYSTEMS

3.1 Introduction

Autonomous vehicles (AVs) are a rapidly advancing technology that will revolutionize numerous aspects of driving: what individuals drive, how they drive, and whether they drive at all. Recently, the evolution of AV technology and readiness for deployment has been rapidly expediting. This is evidenced through the emerging AV OEMs (Original Equipment Manufacturers), such as Google, General Motors, and Uber, who are developing AVs to eventually introduce to consumer markets [36]. Although an exact time line for their deployment is unknown, the introduction of AVs to consumer markets is projected to occur to an overwhelming extent by the 2050's, when 80-100% of sold cars are projected to be AVs [37]. In response to the increasing reality of an AV future, the National Highway Traffic Safety Administration (NHTSA) released the Federal Policy on Automated Vehicles in September, 2016 [38]. This policy includes guidelines for AV manufacturing and regulation. It also recommends means for expediting the introduction of AVs into consumer markets. To bring clarification to the area of AVs, the Society of Automotive Engineers' (SAE) levels of automation were adopted by the NHTSA as the official classification system for autonomous vehicles [39]. These levels range from level 0 (no automation), through level 1 (one automated feature) to levels 4 and 5 (full automation in certain conditions or at all times respectively) [40].

3.2 Literature review

In the past, modeling of numerous aspects of advanced driver assistance systems (ADAS) has been conducted, which has improved AV-related technology knowledge.

As early as 2001, research was completed to evaluate the potential minimum spacing between autonomous vehicles. This was determined to be 30 meters at highway speeds, equating to a highway capacity of 3000 vehicles per hour [41]. In 2007, the placement of ultrasonic sensors in a variety of positions during automatic parking was modeled to develop recommendations for sensor location [42]. For adaptive cruise control, Moon and Yi [43] designed a naturalistic system where the objective was to model the system driving behavior as close to the way humans drive. S. Li et al. [101] proposed a multi-objective vehicular adaptive cruise control system. The system provided significant benefits in terms of fuel efficiency and tracking capability and performed satisfactory driver desired car following behavior. With respect to autonomous lane changing, an algorithm based on the recognition of surrounding features such as vehicle speed and distance was implemented in 2011 [45].The simulation results proved environmental recognition-based lane changing to be feasible. Similar work was done by Schubert el at. [46] who implemented their algorithm in a prototype vehicle. Zafeiropoulos and Tsiotras [47] designed two lane tracking driver steering systems, and compared their performance. They concluded that the system which incorporated driver preference, as compared to the one which did not, performed more efficiently. In 2017, Automatic Emergency Braking System (AEBS) based on the Nonlinear Model Predictive Algorithm, termed the Advanced Emergency Braking System, was modeled [67]. The modeling indicated the proposed AEBS system had higher performance than existing variants

3.2.1 Contributions

This work attempts to build off already conducted research and contribute to AV knowledge through modeling of SAE levels. Despite the detailed modeling of numerous AV applications that has already occurred, research related to definitive SAE levels, as outlined in the Federal Policy on Automated Vehicles, is very limited. This is especially true from the standpoint of taking a bottom-up approach to evaluate the improvement in vehicles based on performance measures of SAE levels. Through explicitly performing this modeling and evaluation of SAE levels, the submitted work makes a significant contribution to AV knowledge; modeling of SAE levels 0 to 5 using a bottom-up approach. The bottom-up approach attempts to explain the proposed impacts of AVs by modeling autonomous functionalities which define each SAE levels. It was prioritized to understand what performance characteristics these levels would bring about in a general road environment and, more specifically, in the AV/CV space.

The decisions made during the modeling process were predicated upon past research in AV modeling. Level 0, representing exclusive human driving behavior and no automation, was modeled with the Intelligent Driver Model (IDM) [52]. This is because it has been shown in previous research that IDM quantitatively replicates the macroscopic and microscopic dynamics of human driving behavior in a straightforward manner [53]. Thus, modeling level 0 with IDM eases the understanding of model operation. Additionally, ACC, or level 1 automation, was modeled with enhanced IDM. Past research has shown that simple IDM models ACC in a highly conservative manner because of IDM's more than required braking reactions when certain maneuvers are included in the modeling [53]. Enhanced IDM is less conservative and serves as a more realistic alternative. At level 2, we add lane-keeping assist functionality. This feature is modeled using using a third-order autoregressive time series [54]. Complete automation at level 3 is accomplished by automating the lane changing functionality. Minimizing Overall Braking Induced by Lane Changes (MOBIL) algorithm is used to model automated lane changing. MOBIL was employed because it has been proven through past simulations that it can model lane changing through employing the computations already completed in the IDM car following model [55]. MOBIL takes its decision variables from car following computations, so there is a very high degree of mathematical consistency. As a result, AV lane changing can be modeled with minimal additional calculations, reducing computational complexity. Level 4 is modeled by designing automated control system for operational design domain and minimal risk conditions. Complete automation architecture is applied for level 5.

We introduce stochasticity to a class of deterministic traffic flow models. The deterministic driving models though a fair representation of the human driving behavior fail to account for the heterogeneity in the driving behavior of different individual drivers. In order to represent the different driving behaviors like conservative, neutral, aggressive and well as reaction time we introduce stochastic parameters to the deterministic traffic flow models [56].

In summary, the main contributions of this work include:

1. To the best of our knowledge this is the first work to study the modeling of each SAE level.

2. The modeling of the SAE level is done using a bottom-up approach.

3. The modeling explores the impacts of SAE levels on traditional as well as non-traditional measures.

4. We conducted penetration studies to evaluate the mobility impacts of various volume mixes.

This paper is organized as follows. Section I presents introduction, literature review and contributions. Section II details the methodology used in our study. In section III we discuss the numerical results and insights. Finally, section IV provides conclusions and future research directions.

3.3 Methodology

To model the SAE levels from bottom-up we designed new traffic flow models using some of the currents models as the base. This includes car following, lane changing and lane centering models. Once the SAE models were formulated we integrated these with VISSIM using an external driver model API. The simulation data was

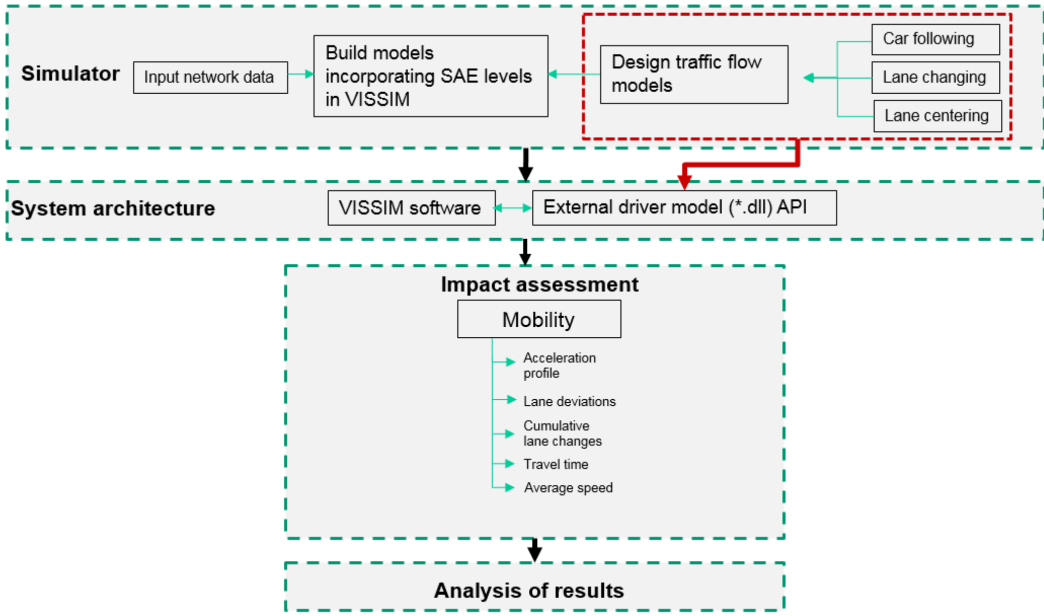

Figure 3.1. Framework for modeling of SAE levels

then used to analyze the impact of the different SAE levels on mobility measure like the acceleration profile, speed profile, lane deviations and lane changes. These measures are then analyzed and the results are interpreted. Figure 3.1 provides a visual description of the framework.

3.3.1 SAE Level Description

The National Highway Traffic Safety Administration has adopted six levels of automated driving systems which range from complete human driver control to full vehicle autonomy. The longitudinal and the lateral control progressively gets transferred from the human to the system from level 0 to level 5. The monitoring of the environment is by the human, in level 1, and 2. On the other hand, for levels 3, 4 and 5, the automated system of the vehicle monitors the driving environment. The system fall backs on the human from level 0 to level 3 but in level 4 and 5 the system is responsible to keep the controls under unexpected circumstances. [40]

3.3.2 Traffic flow models and related components

In this section we will discuss the various models employed to model the human and the corresponding automated driving-related function.These include car-following, lane-centering and lane-changing behaviors.

Car-following models

Human control To model human car-following behavior we employ the intelligent driver model (IDM) [59] . Even though IDM is a simple car following model, it has been shown quantitatively that it models human driving behavior [60]. As the intelligent driver model is a deterministic car-following model we have overcome the limitations to the model by making stochastic extensions to the model by introducing external noise. As preliminaries, we will introduce the IDM and then present the extensions to the model. IDM considers acceleration to be a continuous function, which is affected by numerous. These are the space headway between the vehicle and its leading vehicle, the desired velocity, the current velocity, and the velocity difference of the vehicle from the leading vehicle. The SAE 0 acceleration function is defined by:

$$a_{SAE_0}(a_{IDM}, \epsilon_0) = a_{IDM} + \epsilon_0 \tag{3.1}$$

where, a_{SAE_0} is SAE 0 acceleration and a_{IDM} is IDM acceleration. ϵ_0 is an error term added to the deterministic IDM acceleration to model a stochastic SAE 0 acceleration. ϵ_0 follows a normal distribution with mean as $\mu = 0$ and variance as $\sigma^2_{SAE_0}$ which is non$-$zero and and is uncorrelated with a_{IDM}. The IDM acceleration is given by:

$$a_{IDM}(s, v, \Delta v) = a\left[1 - (\frac{v}{v_0})^{\delta} - (\frac{s^*}{s})^2\right] \tag{3.2}$$

where s the headway between the leading vehicle and the follower, v is the current velocity of the vehicle, δ is the free acceleration component, Δv is the velocity differential between the leader and the follower, v_0 is the desired speed of the vehicle, s^* is the desired space headway. The function for s^* is given by:

$$s^*(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}} \tag{3.3}$$

where, s_0 is the minimum headway space, T is the desired time headway, b is the maximum desired deceleration.

The IDM model tries to mimic car following behavior but is a deterministic model. Since traffic flow has different driver attributes we will introduce stochasticity in IDM to better reflect practical traffic flow conditions at micro level. In order to account for heterogeneity in the values of a, b and T, we have modeled them using log-normal distribution.

We assume that the parameters a, b and T for vehicles follow a log-normal distribution [61, 62]. Therefore for each vehicle the parameters are drawn from the below set of distributions.

$$\log(a) \sim \mathcal{N}(\mu_a,\, \sigma_a^2) \tag{3.4}$$

$$\log(b) \sim \mathcal{N}(\mu_b,\, \sigma_b^2) \tag{3.5}$$

$$\log(T) \sim \mathcal{N}(\mu_T,\, \sigma_T^2) \tag{3.6}$$

The IDM parameters used in the paper are as presented below in Table 3.1. The values/mean of a , b, T, δ, s_0 are taken from [52]. Coefficients of variation of a , b, T is assumed to be 20%.

T is adjusted for the SAE level using the below formulation

$$T_{SAE_k} = \lambda_k T \tag{3.7}$$

Autonomous control Autonomous car-following behavior is modeled using Enhanced IDM model which also simulates ACC feature [52]. This model is an extension of the IDM. However, the Enhanced IDM model is based on the following assumptions; the ACC acceleration is higher than that of IDM and the ACC acceleration is continuous. Below is the formulation for the ACC acceleration.

$$a_{CAH}(s,c,v_l,a_l) = \begin{cases} \frac{v^2 a_l}{v_l^2 - 2s\bar{a}_l}, \text{if } v_l(v - v_l) \leq 2s\bar{a}_l \\ \bar{a}_l - \frac{(v-v_l)^2 \Theta(v-v_l)}{2s}, \text{otherwise} \end{cases} \tag{3.8}$$

$$a_{acc} = a_{IDM}(1-c) + c[a_{CAH} + b\tanh\left(\frac{a_{IDM} - a_{CAH}}{b}\right)] \tag{3.9}$$

Where, a_{CAH} is the constant-acceleration heuristic (CAH) acceleration, v_l is the velocity of the leading vehicle, a_l is the acceleration of the leading vehicle, $\bar{a}_l$is the

Table 3.1. IDM model parameters

Parameter	
Highway Desired speed range (v_0)	55-88 mph
On ramp speed range	25-55 mph
Free acceleration exponent(δ)	4
Desired time gap(T)	$\sim$ Log-normal(0.33,0.2) s
Jam distance((s_0))	6.56 ft
Maximum acceleration((a))	$\sim$ Log-normal(0.31,0.2) ft/s^2
Maximum Deceleration ((b))	$\sim$ Log-normal(0.67,0.2) ft/s^2
Error term ((ϵ_0))	$\sim$ Normal(0.0,0.3) ft/s^2

Table 3.2. Headway Adjustment Factor

SAE Level	0	1	2	3	4	5
Adjustment Factor	1	0.8	0.7	0.6	0.5	0.4

effective acceleration = min (a_l, a) , Θ is the heaviside step function and c is the coolness factor which ranges between 0 to 1. a_{ACC} is always higher than a_{IDM} and the acceleration profile of cars modeled after the Enhanced IDM have a more relaxed response to discontinuous headways which results in improved mobility.

$$a_{SAE_1}(a_{ACC}, \epsilon_1) = a_{ACC} + \epsilon_1 \tag{3.10}$$

$$\sigma^2_{SAE_1} = \sigma^2_{SAE_0}/k \tag{3.11}$$

where, ϵ_1 follows a normal distribution with mean as $\mu = 0$ and variance as $\sigma^2_{SAE_1}$ which is non−zero and and is uncorrelated with a_{IDM}. Here we assume that $\sigma^2_{SAE_1}$ is lower than $\sigma^2_{SAE_0}$ by a factor of k where k is > 1. In our model k = 10.

Lane-centering models

Human control Human control: The lateral position of vehicles under human control, is modeled as an autoregressive time series model [54]. In the time series model, Y_t is the lane position of the car at time t. $Y_t = 0$ when the vehicle is in the center of the driving lane, $Y_t \leq 0$ corresponds to when the vehicle is left of the center lane, and $Y_t \geq 0$ corresponds to when the vehicle is on the right of the center lane. In a first order time series, the vehicle's lateral position depends on the weighted average of the previous three time steps plus a signed error term. Therefore, the formulation for the lateral position for time step t is as below

$$Y_t = \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \beta_3 Y_{t-3} + |e_t| I_t \tag{3.12}$$

$$\log\left(\frac{p_t}{1-p_t}\right) = \gamma_0 + \gamma_1 Y_{t-1} \tag{3.13}$$

Where, Y_t, Y_{t-1} and Y_{t-2} are the lateral positions of the vehicle at time $t-1, t-2$ and $t-3$ respectively, e_t is the error term, which follows a normal distribution, and I_t

is 1 or -1 depending upon the value of p_t which is assumed to have a functional form following the logistic model given in equation 3.13. Dawson et. al [54] calibrated this model which is used in our paper. Δy is the difference between the current lateral position and the future lateral position.

The lateral position is given as an input to VISSIM as an angle instead of the position itself as the API is designed is such a manner. Below is the transformation of the future lateral position to an angle (in radians).

$$\theta_{SAE} = d_{SAE}\theta \tag{3.14}$$

$$\frac{\Delta y}{\Delta x} = \theta \tag{3.15}$$

$$\Delta x = vt \tag{3.16}$$

where, Δy is the difference between the future lateral position and the current lateral position, Δx is the difference between the future longitudinal position and the current longitudinal position , t is the time-step of analysis which is 0.1 seconds. The angle θ therefore, can be approximated as the ratio of Δy with respect to Δx. d_{SAE} is the deviation factor for a particular SAE level ranging from 0 to 1. The lower the value of the deviation factor, lower is the tendency for deviation of the car from the centerline of the lane. Under human control d is assumed to be 1.

Autonomous control For autonomous lane centering we have assumed that $d =$ 0.5 which represents the lane-deviation tendency. A lower lane-deviation tendency under autonomous control is reasonable as the autonomous car will be able to perceive much smaller deviations and immediately take necessary action to center the vehicle.

Lane-changing models

Human control The lane changing model used is MOBIL, a rule-based lane changing model is used as the base model to simulate the added autonomous feature along with probabilistic extensions [55]. Firstly we discuss MOBIL and then introduce a probabilistic lane changing decision rule. MOBIL considers two criteria for lane change; 1) safety criterion, where the vehicle behind the vehicle which changes lanes will not require to brake more than a safe level of deceleration and 2) incentive criterion, where the vehicle changes lane only if the below condition holds

$$a'_c - a_c + p(a'_n - a_n + a'_o - a_o) \geq \Delta a_{thr} \tag{3.17}$$

$$a_n \geq -b_{safe} \tag{3.18}$$

where, c is the vehicle considering to change lane, n is upstream vehicle on the target lane, o is the upstream vehicle on the present lane, a_c is the acceleration of vehicle c on the current lane, a'_c is the acceleration of vehicle c on the target lane, a_o is the acceleration of vehicle o before lane change by vehicle c, a'_o is the acceleration of vehicle o after lane change by vehicle c, a_n is the acceleration of vehicle n before lane change by vehicle c and a'_n is the acceleration of vehicle n after lane change by vehicle c, p is the politeness factor. Δa_{thr} is the acceleration threshold that must be crossed in order to make a lane change. This threshold exists to make sure that a lane changing operation by a vehicle is made only when the overall weighted acceleration of the group of vehicles is above a certain level. This helps in a lower adverse impact on the neighborhood vehicles' movement. For humans we have assumed the Δa_{thr} to be 3.

The politeness factor p represents the level of altruism of the driver who wishes to change lane. A politeness factor of 1 is a highly altruistic person who considers the effect of lane change on other vehicles' and politeness factor lower than 0 is a selfish person who is ready to adversely affect his own acceleration if that sufficiently reduces the accelerations of the affected vehicles. An improvement over the MOBIL model has been attempted in this paper where once a vehicle initiates lane change, in that scenario two vehicles ahead and two behind the vehicle will not initiate until the current vehicle's maneuver is completed. We used a politeness factor of 0.5, a more realistic value for the parameter. Politeness factor of 0 represents a person who is completely selfish and 1 represents an altruistic driver. Therefore, we assume on an average the driver's nature is between the two extremes.

Autonomous control For autonomous lane changing we assume that the Δa_{thr} = 2, a value lower than the Δa_{thr} for humans.We make an assumption that Δa_{thr} for humans is greater than Δa_{thr} as the system in autonomous mode will be able to perceive mobility-enhancing opportunities by changing lanes better than humans. This is motivated by the fact that autonomous systems will have more accurate perception of the traffic conditions.

3.3.3 Mapping of SAE Levels to Driver Models and Driving Features

In the mapping of SAE levels to driver models/features, the key factors for consideration in each automation level are presented. The investigation of the SAE levels are conducted in a microscopic, multilane simulator called VISSIM. The microscopic simulations allow for parameters to be specified in detail. The External Driver Model (EDM) DLL interface allows the user to replace the driving behavior by a fully user-defined behavior for some or all vehicles in a simulation run. The EDM interface was used to model the various SAE levels.

SAE Level 0

Level 0 represents no automation and hence is considered to be equivalent to human driving with no assistance. The paper models this SAE level using a stochastic extension of IDM as the car following model. The lane centering is modeled using the third order autoregressive time series with human control parameters. The lane changing model uses the MOBIL algorithm with acceleration threshold parameter for humans.

SAE Level 1

In Level 1, either steering or acceleration/deceleration behavior is automated under the ODD. In this research, SAE level 1 is modeled by introducing automated acceleration and deceleration by means of Adaptive Cruise Control (ACC) in the vehicle. ACC is modeled in the paper using a model which employs a stochastic version of the Enhanced IDM model [52] . The model is an improvement over the IDM model, which is primarily designed for a single lane car following behavior and hence responds conservatively in a situation where the space headway changes non-continuously, for example in the case of cut-in maneuvers. Enhanced IDM extends IDM using a constant acceleration heuristic (CAH) which implements a less constrained reaction to cut-in maneuvers.

SAE Level 2

Level 2 automation involves automating both steering and acceleration/deceleration under certain conditions. The paper models Level 2 by means of ACC and lane-keeping assist. The lane centering feature is modeled using a third-order autoregressive time series model with parameters for autonomous control [54].

SAE Level 3

Level 3 automation translates to fully autonomous behavior in certain conditions. Control is given back to the driver when pre-specified conditions for automation are not met. In our study this level is modeled by assuming that a vehicle is fully autonomous in a highway environment only. If the vehicle exits these conditions, the control is given back to the driver. while in a fully autonomous state the car-following, lane-centering as well as lane changing features are automated. While modeling the different SAE levels one of the key features for the levels until SAE 3 automation is the need for transition of control between the system and human. There are a few recently studies which have looked into the transition of control and reaction times [57, 58]. We have used the data from these studies to model the reaction time of the drivers during transition of control.

SAE Level 4

– Level 4 automation implies that the vehicle is completely autonomous while operating within it's operational design domain (ODD) [39]. The vehicle will transition to a low-risk operating mode for example lowering its desired speed when outside the ODD which we will define as the Minimal Risk Conditions Desired Speed (MRCDS). In this paper we assume ODD as any roadway with clear lane marking. The vehicle enters a minimal risk operating condition when the lane markings are not clearly visible. We study the impact on traffic while the vehicles travel both inside and outside the ODD.

SAE Level 5

– Level 5 automation is the highest level of automation among the various SAE levels. This level of automation involves the vehicles having control under all type of conditions. These include sections of the roads where the lane markings are not clear, signs are non-standardized among others.

3.4 Results

We present the results of SAE mobility modeling for two networks. The first network is as illustrated in Figure 3.2 designed for the simulations is a 1.5 mile straight two-lane highway with a single-lane on-ramp joining the highway at 0.3 mile. Traffic from on-ramps into the highway are typical scenarios for traffic congestion and bottlenecks and hence this particular network was chosen to analyze the performance of different SAE levels in such a network. The traffic flow on the highway is assumed to be 800 veh/hr/lane and the traffic flow on the on-ramp is 300 veh/hr/lane. The speed distribution of the vehicles is 50mph to 80mph.

Given this network, we have identified two unique type of traffic flows that can be analyzed given the network; 1) vehicles originating on the highway and continue traveling on it 2) vehicles entering the highway through the on-ramp. In this paper we present the impacts on the these flows for each of the SAE levels. Below we discuss the impacts of various SAE levels and then analyze the impacts for different penetration levels.

The above network scenario accounts for traffic interactions in highway settings. In order to have more comprehensive analysis of the traffic impacts of different autonomous levels, we also look at an signalized intersection setup. Signalized intersection account for the highest amount of traffic delays in cities. Therefore, an analysis of such a setting will give us a more holistic view of the impacts of autonomous vehicles in different scenarios. The chosen intersection consist of a major and a minor approach. The major approach consist of 3 through lanes of which one of them becomes a left turning storage area. The minor approach consist of 2 through lanes of which becomes a left turning storage area. The right turning movement is controlled by yield sign. The volume assumed is 500 veh/hr/lane. The speed distribution of the vehicles is assumed to be between 30mph to 40mph.

The traffic is composed of cars which are of length 12 ft and width 4.5 ft. We have chosen a homogeneous traffic to be able to analyze the effects of the various SAE levels on the traffic. Also the simulations for each SAE level vehicles was run separately assuming 100% penetration of the particular SAE level vehicle. For each SAE level there was a vehicle type created in VISSIM as shown in Figure 3.3. The created vehicle types were linked to EDM DLLs as a shown in Figure 3.4.

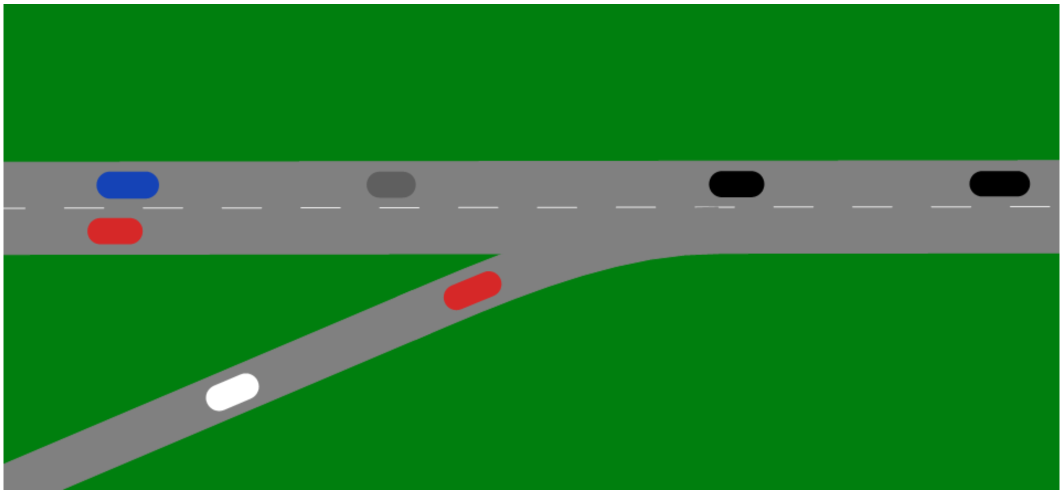

Figure 3.2. Illustration of a highway segment with an on-ramp

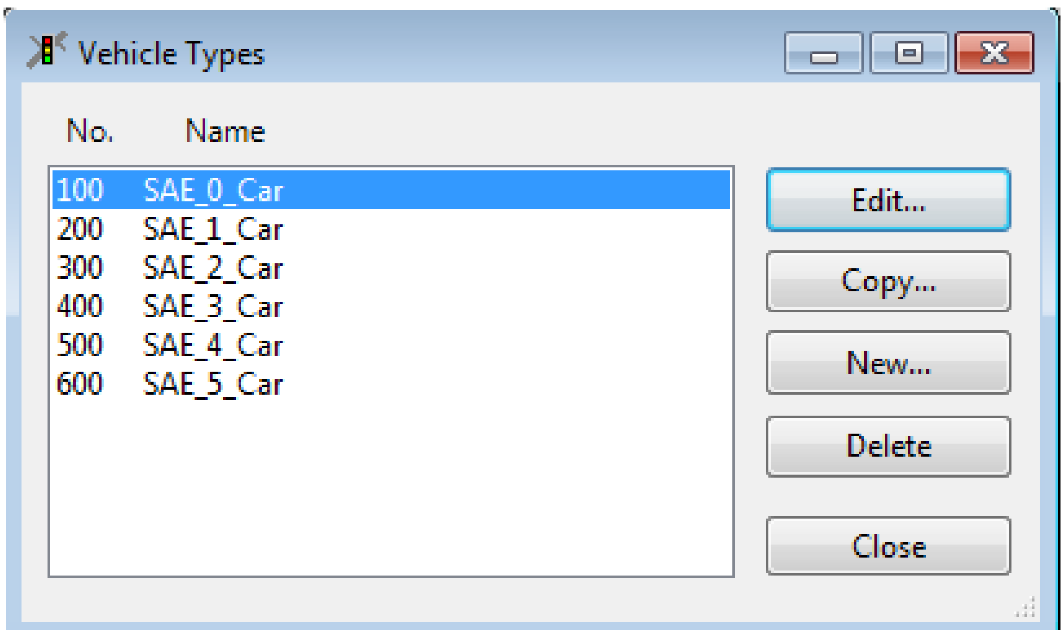

Figure 3.3. Vehicle types defined in VISSIM

3.4.1 Highway Scenario

In this section we discuss the results obtain from simulation run on the highway network.

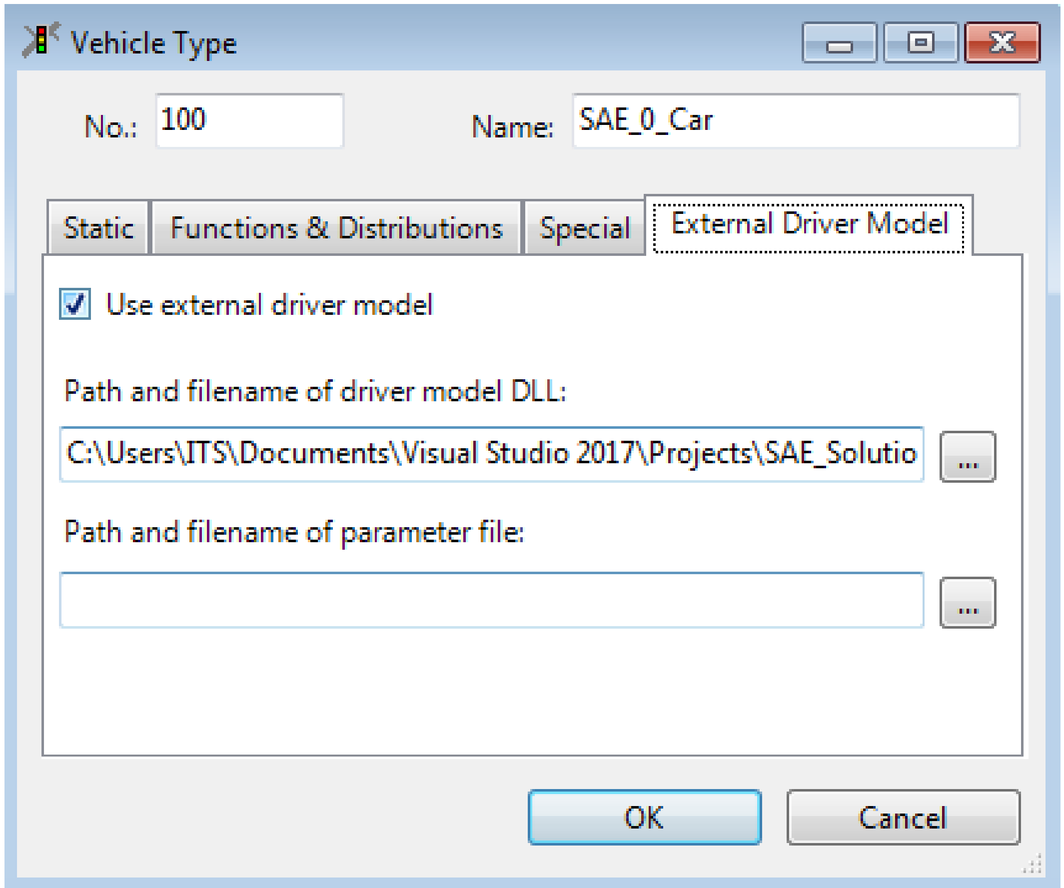

Figure 3.4. External driver model linked to each SAE level

SAE level impacts

Below we present the results categorized by the different SAE levels analyzed.

SAE 0 and SAE 1 Figure 3.5 plots the speed profile of SAE 1 vehicles on the highway for different levels of coolness factor c and compares them with the speed profile of SAE 0 vehicles. From the enhanced IDM formulation we know that, as coolness factor c increases the braking response to discontinuous headways reduces. At 0.3 mile there is an on-ramp because of which the vehicles on the highway as well as the ones on the on-ramp end up experiencing non-continuous headways as their predecessor change on account of the merging activity. The vehicles experience

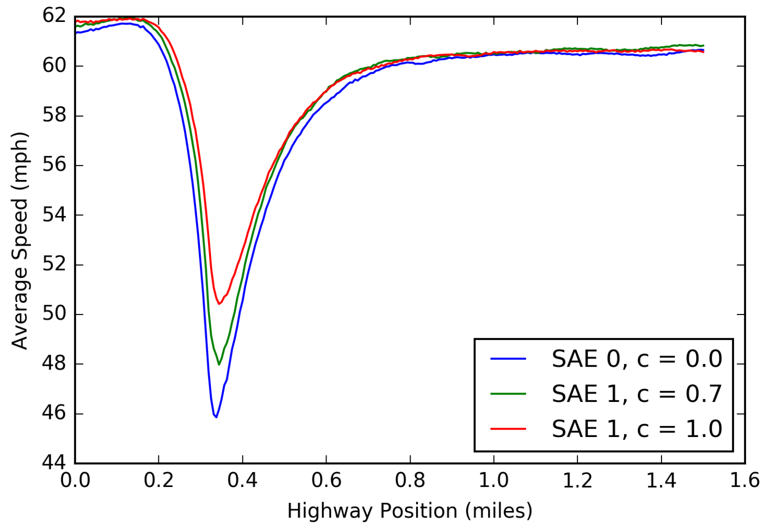

Figure 3.5. Speed profiles of SAE 0 and SAE 1 vehicles (with different coolness factors)

deceleration as they approach the point of entry where the on-ramp merges with the highway. It is observed that the maximum deceleration of the through vehicles is at the point at which the on-ramp merges with the highway. SAE 1 vehicles with higher c are able to negotiate this segment of the road with higher effectiveness without having to brake as much as SAE 0 and SAE 1 vehicles with lower c. We can see this from Figure 3.5 that as the value of c increases the minimum speed that the vehicles decelerate to increases and hence results in higher mobility. Once the vehicles cross the merging section they start picking up speed after the merging operation is completed to match the desired speed on the highway. The minimum speed of SAE level 1 vehicles with $c = 1$ is 50.5 mph whereas the minimum speed of SAE level 1 vehicles with $c = 0$ is 46 mph. The speed profile across the highway section shows that the SAE level 1 vehicles with higher c travel faster than the SAE level 0 vehicles at all points on the network. Hence we conclude that SAE level 1 vehicles under autonomous longitudinal control experience higher mobility as compared to SAE 0 level vehicles under human control.

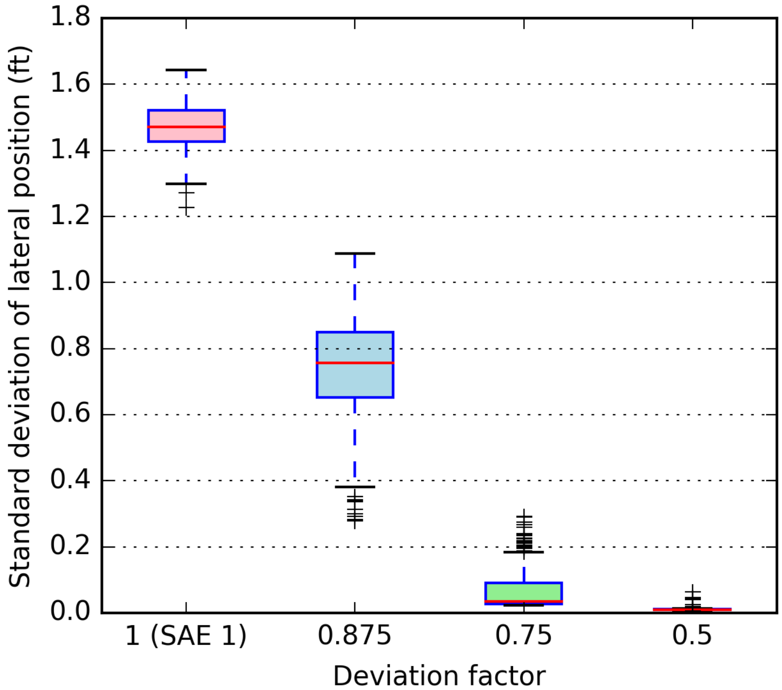

Figure 3.6. Box pot of the standard deviation of lateral position of SAE 1 and SAE 2 for different deviation factors

SAE 2 Figure 3.6 compares the standard deviation of the lateral position of SAE 2 vehicles across the entire stretch of the segment with different levels of deviation factors. The fist box plot in the figure from the left is the standard deviation under human control. As we go towards the right with decreasing deviation factor we observe the mean value of the deviations reduce and the spread of the range also narrows down.This clearly shows that as the deviation factor is reduced the vehicles travel much more closer to the centerline of the lanes enhancing safe driving behavior. As the lateral control is with human in SAE 0 and SAE 1 we see higher deviations in those vehicles as compared to the lateral deviations of SAE 2 vehicles.

SAE 3 Figure 3.7 shows the impact on lane changes as the acceleration threshold in the MOBIL algorithm is changed. The number of lane changes decrease significantly

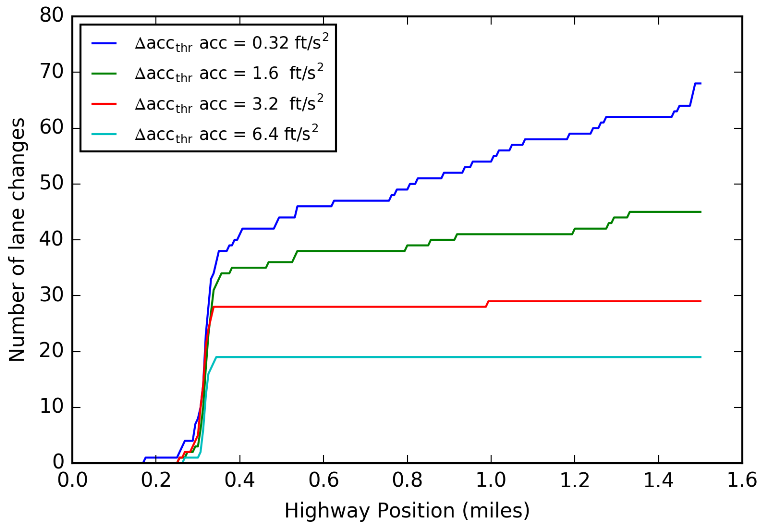

Figure 3.7. Total number of lane changes for different levels of threshold accelerations for SAE 3 vehicles

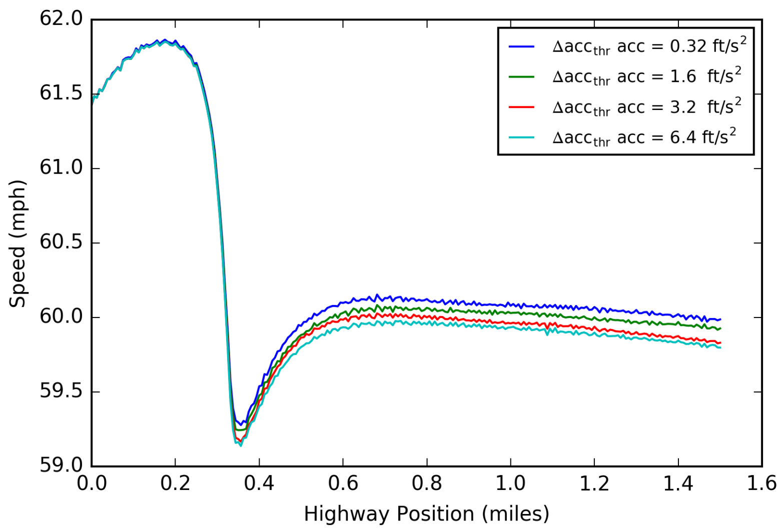

Figure 3.8. Speed profile for different levels of acceleration thresholds

as the acceleration threshold a_{thr} increases. A significant increase in a_{thr} especially in semi-congested traffic situations can result in reduced mobility.

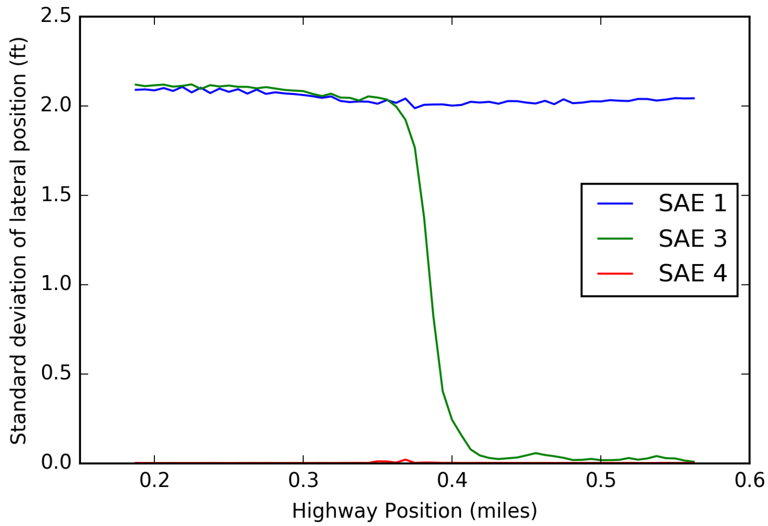

Figure 3.9. Change in lateral deviation with shift in control from human to autonomous

SAE level 3 is characterized by the option of transferring control between human and the system. In our model we have assumed that SAE level 3 the vehicles are completely autonomous on highways and not otherwise. In our particular network, the vehicles that enter the highway from the on-ramp are initially under human control as they enter. The control is then transferred to the system based on reaction time from previous studies [57, 58, 63]. We have assumed that both the time taken for taking control from the autonomous system and giving control to the autonomous system follow log-normal distributions. In figure 3.9 we have plotted the standard deviation in lateral position for SAE 1, SAE 3 and SAE 4 vehicles. We can see that for SAE level 3 vehicles as cumulative number of vehicles in autonomous control increase the standard deviation of the lateral position gradually reduces and converges to that of SAE level 4 vehicles.

SAE 4 and SAE 5 SAE 4 level vehicles are completely autonomous in ODD and operate at minimal risk conditions when they are outside their operational design

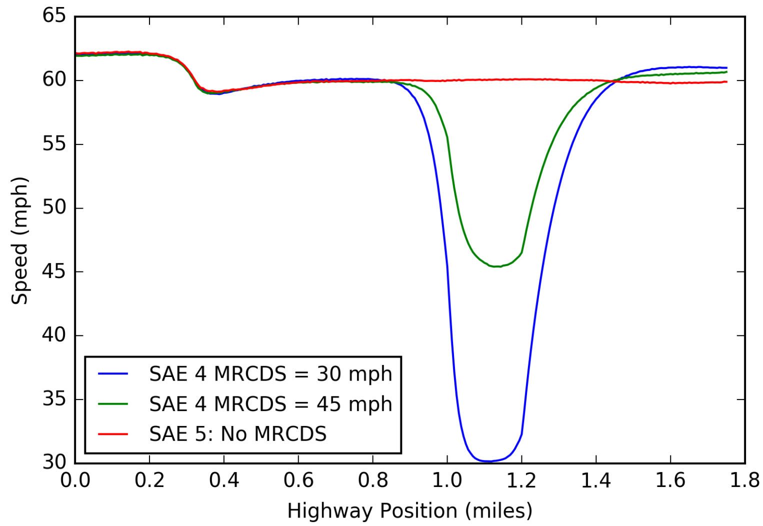

Figure 3.10. speed profiles for different minimal risk speeds in unclear lane markings area

domain. In our study we assume that SAE 4 level vehicles' ODD is any roadway with clear lane markings. To understand how SAE level 4 vehicles adjust to non-ODD conditions, for the purpose of our study we simulate a roadway condition where the lane markings are unclear from 1 to 1.2 mile segment on the highway. As the SAE level 4 vehicles enter the unclear markings road segment they need to reduce their desired speeds significantly in order to satisfy minimal risk condition. We look at the impact on SAE 4 level vehicle mobility depending on the minimal risk condition desired speed (MRCDS) they need to acquire. Figure 3.19 shows the speed profile of SAE 4 level vehicles for various minimal risk condition speed levels as compared to SAE 5 level vehicles. We observe that the speed profiles monotonically fall as defined minimal risk speed for SAE 4 level vehicle decreases outside the Operational Design Domain decreases.

Penetration impacts

SAE 0 and SAE 1 Here we look at the mobility impacts for various penetration levels of SAE 0 and 1 vehicles. As can be seen from Figure 11, the minimum speed for SAE 0 vehicles is 57.6 mph. We see that for 20% penetration of SAE 1 vehicles improves the minimum speed to 58.5 mph. We can see that as we increase the penetration of SAE 1 vehicles the improvement in speed are not as much as it was for lower penetration. This is because even a small percentage of vehicles with superior mobility maneuvers can improve the overall traffic mobility.Therefore, we can say that even low penetrations of autonomous vehicles on roadways will improve traffic mobility significantly.

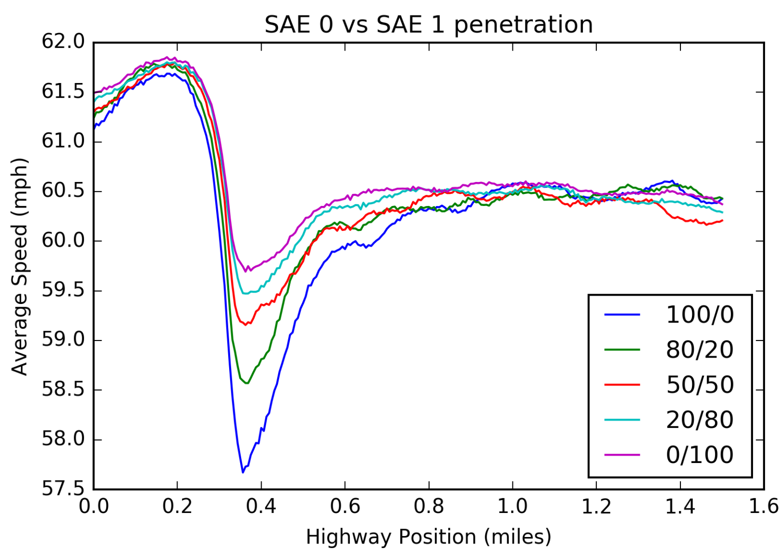

Figure 3.11. Speed profiles for different penetrations of SAE 0 and SAE 1 vehicles

SAE 1 and SAE 2 The IQR of lateral deviation of SAE 1 vehicles ranges between 2 to 2.2 with a median at 2.1 as can be seen from Figure 12. We see that for 20% penetration of SAE 2 vehicles the IQR range increases on the lower end. The IQR range is maximum when the penetration is 50%, which is expected as half the vehicles have the deviation factor 1 and other half have deviation factor of 0.5. The IQR range decreases after this as most of the traffic is dominated by SAE 2 vehicles. Finally under 100% SAE 2 penetration the IQR ranges between .25 to .28. As the penetration of SAE 2 increases, we see that the median falling from 2.1 to 0.26.

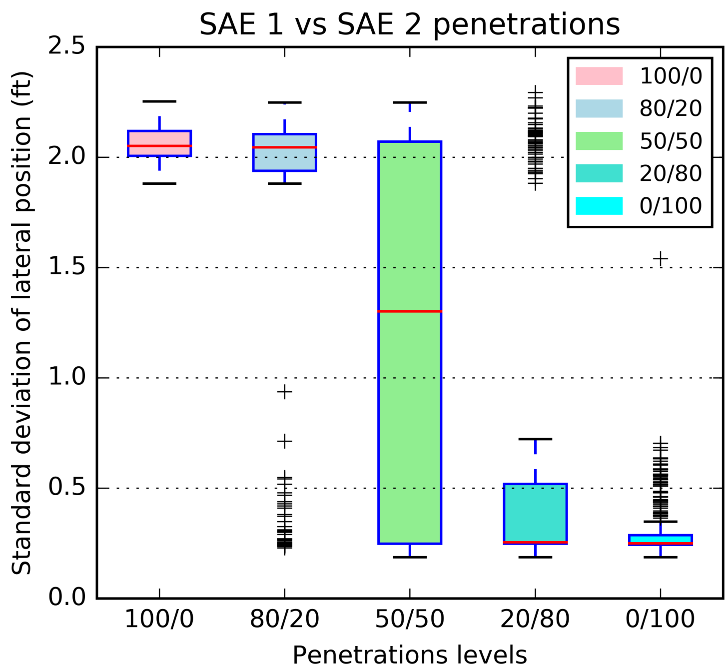

Figure 3.12. Standard Deviation for different penetrations of SAE 1 and SAE 2 vehicles

SAE 2 and SAE 3 In this section we analyze the mobility improvements in traffic with increasing penetration of SAE 3 vehicles due to superior lane changing maneuvers. From Figure 14, we see that lane changing maneuvers from AVs improve mobility. At the same time we see that this improvement is not as significant as compared to improvement seen in longitudinal control was transferred to AVs. Therefore we have looked at the scenario for only 50% penetration. We see that the improvement in mobility is not in proportion to the penetration levels. This is further corroborated by Figure 13 which shows the cumulative number of lane changes for the three different scenarios. At 50% penetration the number of lane changes is lower than expected.

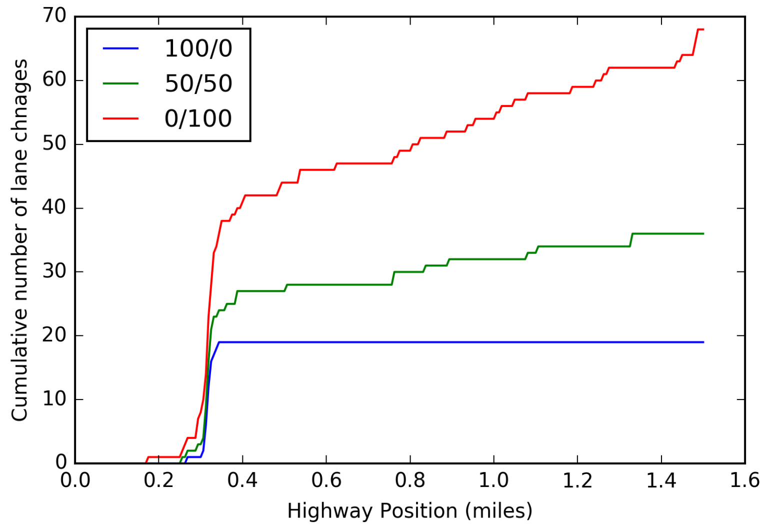

Figure 3.13. Cumulative lane changes for different penetrations of SAE 2 and SAE 3 vehicles

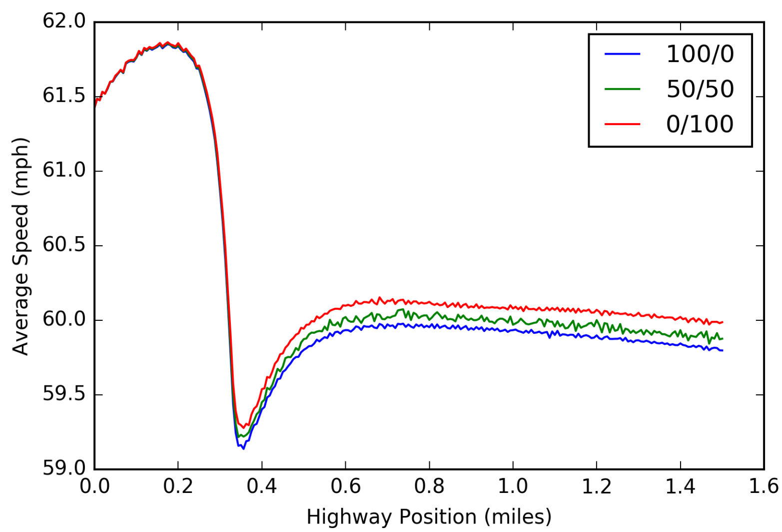

Figure 3.14. Speed profiles for different penetrations of SAE 2 and SAE 3 vehicles

SAE 3 and SAE 4 In this section we look at the impact on traffic characteristics for various penetration for SAE 3 and SAE 4 vehicles. From Figure 15, we can see that the range of standard deviation for 100% penetration of SAE 3 vehicles has an IQR of 0.8 to 0.9 and the median value is at 0.85. When there is 20% of SAE 4 vehicles the IQR range increases from 0.75 to 0.88 and the median value decreases 0.81. When the SAE 4 penetration increases to 50% in that scenario the IQR range is the highest, ranging from 0.1 to 0.8 and the median value at 0.55. The penetration increases to 80% the IQR range decreases significantly ranging from 0.1 to 0.38 with the median 0.11. At 100% penetration we can see that the IQR range expectedly is in the range 0.08 to 0.12 and the median is at 0.1.

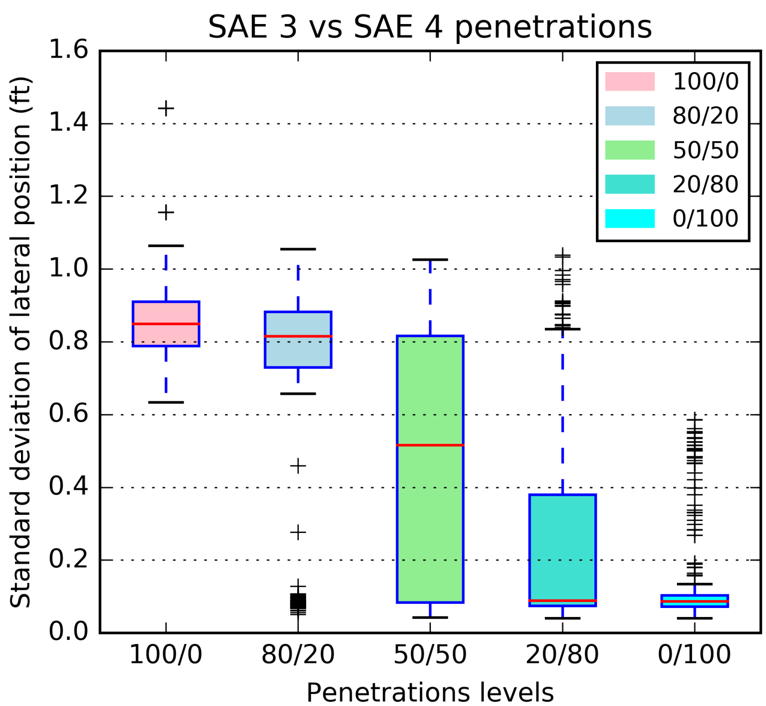

Figure 3.15. Standard Deviation for different penetrations of SAE 3 and SAE 4 vehicles

SAE 4 and SAE 5 In this section we analyze the impact of various SAE 4 and SAE 5 volume mixes on traffic mobility. As mentioned before mile 1 to mile 1.2 is a region with unclear lane markings. Therefore, for SAE 4 this region will be outside the ODD. Here we look at how the speed profiles are impacted for various penetration levels of SAE 4. We see that for 20% penetration for SAE 4 the overall mobility impact on the traffic is significantly high. Especially the extent of this impact can be seen when it is compared to the mobility impact due to further penetration of SAE 4 vehicles. This implies that small penetration levels of SAE 4 vehicles when outside their ODD can result in notable impact on traffic mobility.

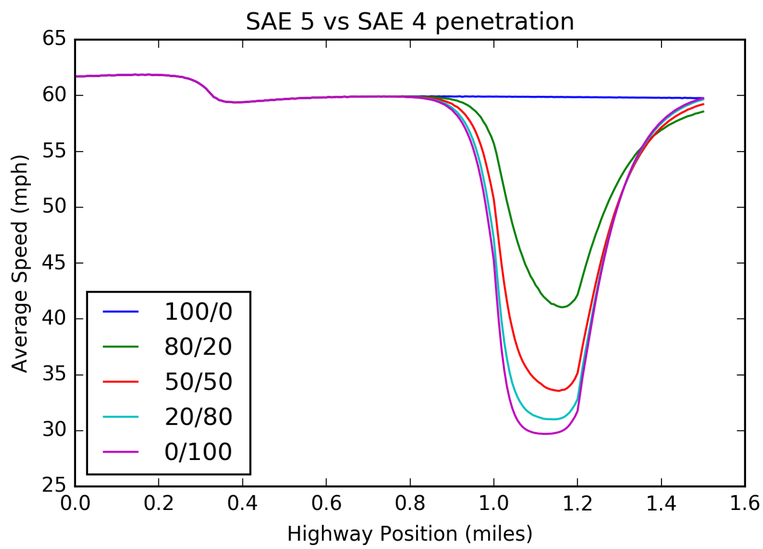

Figure 3.16. Speed profiles for different penetrations of SAE 4 and SAE 5 vehicles

3.4.2 Intersection Scenario

In this section we analyze the mobility impact related results in an intersection setup. We have identified measures of effectiveness (MOE) which particularly reflect the improvements that results due to increased levels of autonomy. We have chosen volume throughput, queue length and number of vehicle stops as the MOEs to evaluate mobility impacts. As can be seen from figure (VT) the throughput increases by 25% from SAE level 0 to SAE level 5. Therefore, we can see that the capacity of the roadways can increase significantly as the autonomous vehicle penetration increases. In figure (QL), we have calculated the average as well as the maximum queue lengths across the different SAE levels. We observe that the queue length show a decrease for the average as well as maximum measures. In the figure (NS) this stop and go behavior of vehicles while waiting in the signal is calculated. It can be seen that the stop and go behavior decreases significantly as the SAE levels increase.

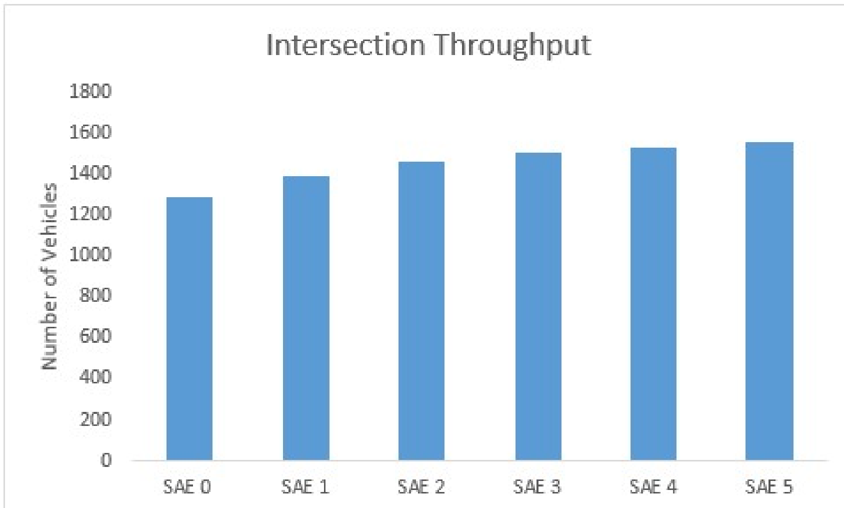

Figure 3.17. Volume throughput at intersection for different SAE levels

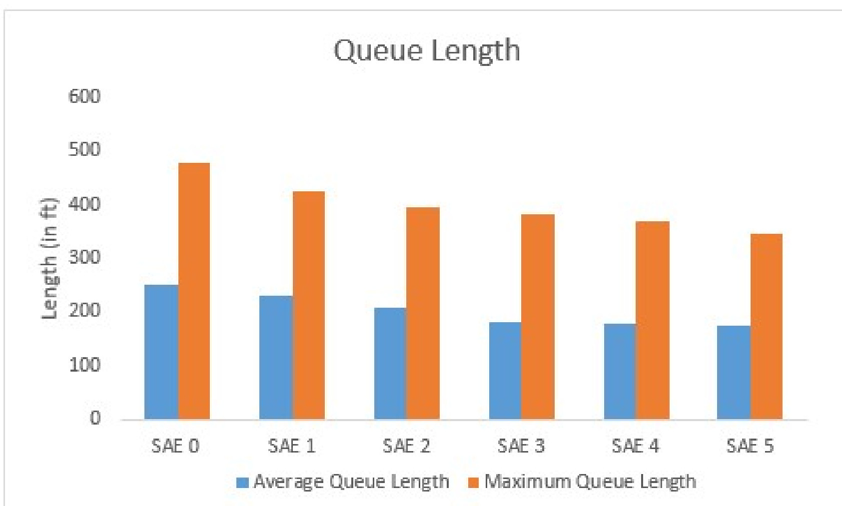

Figure 3.18. Queue length at intersection for different SAE levels

Figure 3.19. Number of stops at intersection for different SAE levels

3.4.3 Conclusions

This paper makes a significant contribution in the modeling of SAE levels. The analysis of performance aspects of SAE levels 0, 1, 2, 3, 4 and 5 was conducted with a bottom-up modeling approach. This is a first of its kind approach to AV research. Level 0 was modeled with the IDM car following model. Level 1, featuring adaptive cruise control, was modeled with the Enhanced IDM Model. Data from simulations of level 1 exhibited a significant improvement in mobility over that of level 0. Level 2, featuring automated lane centering and ACC, was modeled with the Enhanced IDM Model and a third-order autoregressive time series model for lane centering. Level 2's performance indicated it provided or far more stable mobility than levels 1 and 0, which would result in less accidents. Level 3 represented the synthesis of level 2's automated features with automated lane changing enabled by modeling with MOBIL. The automated lane changing prompted a higher rate of lane changes than lower levels, providing for more efficient traffic movement. We observe that for SAE level 4 there can be a negative impact on the traffic flow due to transition to minimal risk condition under poor lane markings. SAE level 5 is able to overcome these traffic disruptions and oscillations and has a smoother velocity and acceleration profile. Together, the modeling of SAE levels 0, 1, 2, 3, 4 and 5 indicates that AV features, are capable of yielding significant benefits from the standpoints of safety and mobility. We also studied the mobility impacts on traffic for various mixes of SAE levels. The results show interesting patterns for the various penetration tested. This validates the applicability of AVs to infrastructure systems through confirming the magnitude of their positive impacts on safety and mobility.

This work will be an asset for practitioners, policymakers and researchers to perform capacity analysis and highway design as the autonomous future becomes a reality. The model can accommodate different mixes of traffic, and therefore the work can also be used to test the impact of various permutations of SAE level penetrations. With this work as a foundation, extensions of future work can be in multiple areas. Research divisions at OEMs can assess the mobility impacts of autonomous vehicles by calibrating this model with their design specifications. Our model can be used as a platform to integrate new ADAS features and evaluate their impact on traffic.

4. RISK EVALUATION OF AUTONOMOUS VEHICLES

4.1 Introduction

Autonomous vehicles are going to usher in significant benefits including safety mobility, environmental and congestion [65]. One of the main selling points of AVs which has been touted by Original Equipment Manufacturers (OEMs) are the safety benefits which multiple automated functionalities bring in to driving [66]. There are sensing technologies like Light Detection and Ranging (LIDAR), Radio Detection And Ranging (RADAR) along with in-vehicle cameras which constantly monitor the environment and use this information to make driving decisions [67], [68]. These driving decisions include a host of features like Adaptive Cruise Control (ACC) [69], Lane change assist [70], Lane Centering, Automatic Emergency Breaking, Red Light Warning etc [71]. Human error in driving accounts for over 90% of accidents on roadways [72]. The main contributors of these errors are contributed by decision error, recognition error and performance error. Automated technologies can over come these human errors by using highly accurate sensors and superior machine vision technology. Federal and state agencies have also agreed to the contribution AVs will have in improving safety levels [73]. As per one statistic AVs can save 30,000 lives a year. Coming to terms this fact NHTSA issued a guidance policy which outlined the direction for testing and implementation of AVs on roadways [74]. One of the key industries which would be impacted by these revolutions is the motor insurance industry [75]. Insurance industry has traditionally used demographic factors in order to price premiums for drivers. This has been a practice which has been going on for a very long time. New innovation to insurance pricing methodology have been introduced lately such as “Pay as you drive” which charges the drivers based on the mileage driven by them [76]. But this does not differentiate between risky and non risky drivers. Further improvements in pricing solutions have been introduced in the last decade due to the access to data which characterizes driving behavior. This is called "Telematics".There has been a surge in telematics based insurance pricing as it tries to accurately capture driver behavior by using driver trajectory [77]. As the penetration of AVs increase on the roadways there is a great need to re-look at the pricing standards the insurance firms are using right now. They also need to re-evaluate the risk of these new types of vehicles on roads.

4.2 Literature review

4.2.1 Insurance pricing

Generalized Linear Models (GLM) have been the traditional mode of risk analysis done for drivers using their demographic data [79], [78]. GLMs are flexible generalization of ordinary linear regression that allows for error terms to have a distribution other than normal. Recently with the introduction of innovative insurance pricing schemes like "Pay as you drive", has paved a need for more higher resolution data [80], [81]. Telematics has been instrumental in providing the big data required by the machine learning algorithms behind the innovative pricing schemes [82]. [83] used machine learning methods to identify risky drivers vs. non risky drivers. While doing so they used accident data from multiple sources and used multiple machine learning methodologies like SVM, Random Forest and Neural Networks have been used in order to build models to predict risky behavior of drivers. Similarly, [84]used K means clustering SVMs to differentiate driver behavior. [85] provided a framework to use smart phone data for analyzing traffic data and usage based insurance. [86] used telematics data to classify drivers profile in car insurance pricing in the German market. [82] in their paper provided a background for the need for telematics data and also listed out the top UBI solutions which have been implemented world wide. VTPI analyzed the feasibility cost and benefits of distance based vehicle insurance [87]. [88] used gradient booting trees for auto insurance loss cost modeling and prediction. Multiple papers have analyzed different machine learning algorithms to predict frequencies and severities [89] - [90] . Therefore, on one hand there have been numerous works which have modelled insurance risk but on the other hand a significant part of it has been done behind closed doors due to competitive nature of the industry [91] - [94]. Publicly available research papers on usage based insurance is less due to the unavailability of accident data. On top of it usage based insurance related research on AVs has not been done due to the unavailability of the data.

Conflict analysis

Surrogate measures of safety have been widely employed when accident data is scarce under the framework of conflict analysis in microsimulation models [95] - [96] . Among the various surrogate measures include Time to Collision (TTC), Post Encroachment Time (PET), MaxS, MaxD etc [99] . There have been multiple indicators of modified versions of the above measures. TTC stands out as the measure which has been used in multiple studies. SSAM is a software designed by FHWA to evaluate conflicts in micro-simulation data which takes in trajectory information from softwares including VISSIM. [100] analyzed aggressive drivers using micro simulation combining SSAM and VISSIM. They modeled normal and aggressive drivers on VISSIM by changing the parameters in the software. [101] built a crash prediction model based on the conflicts framework and micro simulation in the freeway interchange areas. They created a new index which combines TTC average value and the severity of the accident from standard classification table and data collected from Maqun interchange in northeast Nanjing. [102] did a study if VISSIM and SSAM provide good predictability for field measured conflicts at intersections. They did a two step calibration and were able to predict the conflicts to a reasonable extent on 8 signalized intersections.

4.2.2 Contributions

Risk prediction of AVs for SAE levels has not been attempted before due to the unavailability of different autonomous level naturalistic trajectory data. Our work creates a framework to identify no risk, low risk, medium risk and high risk drivers for various SAE levels. Based on our previous work on SAE modeling we used the micro simulation platform to simulate AVs and extract from it's trajectory data for various SAE levels. This trajectory information is used to feed into the SSAM software to identify conflicts which map the drivers to different risk categories. In order to create a data driven model which predicts driver risk for different SAE levels, the above supervised data is used to train and test different machine learning models. Due to the stochastic nature of the various SAE level models, each of the SAE class contains different risk level drivers, This is to simulate real life scenario where different OEMs will have different specifications for each SAE class.

In summary, the main contributions of this work include:

1. To the best of our knowledge this is the first work to study the safety impacts of each SAE level.

2. A prediction model which classifies each driver into various risk categories for every SAE level.

This paper is organized as follows. Section I presents introduction, literature review and contributions. Section II details the methodology used in our study. In section III we discuss the numerical results and insights. Finally, section IV provides conclusions and future research directions.

4.3 Methodology

Below are the components integral to the part of the framework which would be discussed in detail.

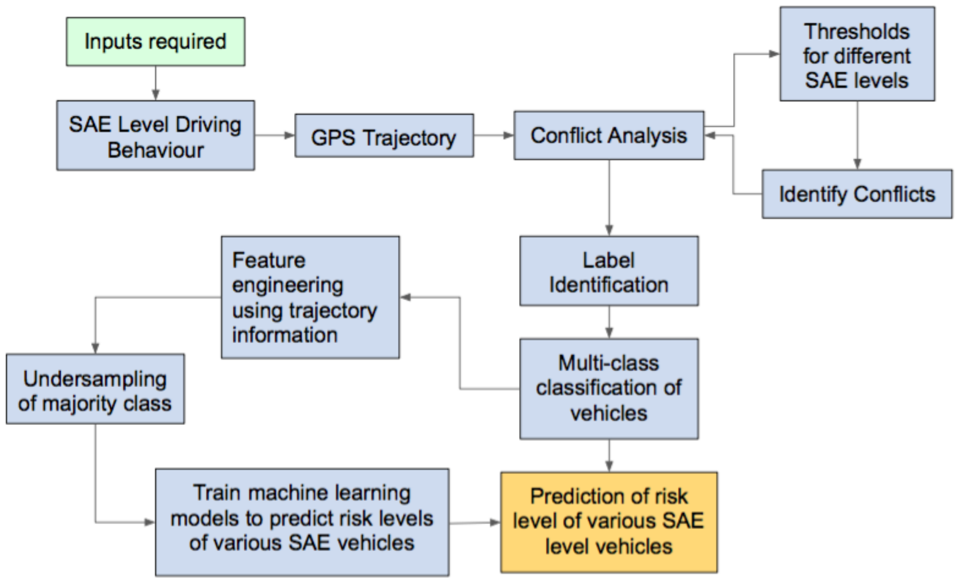

Figure 4.1. Framework for risk identification of AVs

4.3.1 VISSIM

VISSIM is the base platform we use to simulate the different autonomous level vehicles. An External Driver Model (EDM) is used to communicate with VISSIM. The external driver model constitutes of formulation for the various SAE levels from 0 to 5. This EDM controls the car- following, lane changing and lane centering behavior of the vehicles in the simulation to an extent determine by SAE level. VISSIM is a useful software to use for our purpose as it seamlessly integrates any external model other then the default model used by the micro simulator.

4.3.2 SAE Levels

In this section we will discuss the various SAE levels and the models used to mimic them

SAE 0

SAE 0 represents complete human control and this is modeled using intelligent driver model (IDM). IDM has been proved to model microscopic and macroscopic human driver behavior. IDM is a simple model with few parameters to be estimated and hence is a handy model. We have added stochasticity to the IDM model to represent real life variation is driving behaviours.

SAE 1

In SAE 1, lateral control or longitudinal control is automated. In our model we automate the car following behavior using enhanced IDM. Enhanced IDM has been shown to respond less conservatively to non continuous headways and hence provide higher mobility.

SAE 2

In SAE 2, longitudinal and lateral control is automated. In our model we automate the car-following and lane keeping behavior using enhanced IDM and a third-order time series based lane centering algorithm.

SAE 3

In SAE 3, we completely automate the vehicle by adding automated lane changing feature using MOBIL as the base model to the above mentioned features. On freeways the automated mode is active while on the freeways. In an arterial setting the vehicle is autonomous under 30 mph.

SAE 4

In SAE 4, we completely automate the vehicle while it is in it's operational design domain (ODD). That is the vehicle is completely autonomous under regular weather conditions and clear road markings and signage.

SAE 5

In SAE 5, the vehicles is completely autonomous under all conditions.

4.3.3 TTC for SAE Levels

Time to collision (TTC) is one of the most common measures which is used as a surrogate for safety. A lower value of TTC signifies higher chances of collision. TTC formula is as below:

$$TTC = \frac{p_i - p_j}{v_i - v_j} \tag{4.1}$$

Where i is the leader and j is the follower. p_i is the position of the leader and p_j is the position of the follower. v_i is the speed of the leader, v_j is the speed of the follower. Lower value of TTC indicates a higher chance of an accident and hence would be qualified as a more critical conflict. TTC values under a certain threshold (based on literature) are considered as risky. For autonomous vehicles these thresholds which are used generally for human drivers need to be adjusted to accurately reflect the right conflict severity. We modify TTC threshold formulation to account for different SAE levels.

The TTC thresholds have been defined between the range 0.1 to 6 secs in many studies. We use this range in order to define 3 different thresholds of TTC for human drivers. TTC less than 1.5 secs indicates high risky behavior, TTC between 1.5 secs to 3 secs is defined as medium risky behavior. TTC between 3 to 5 secs indicates low risky behavior. TTC above 5 secs is considered no risk. The above definition for TTC thresholds are for human drivers. In order to define the TTC threshold for different SAE levels we provide the below formula.

$$TTC\_threshold_{SAE\ level\ j} = TTC\_threshold_{SAE\ level\ 0}(1 - \sum(I_j)) \tag{4.2}$$

I_j is the improvement in safety due to SAE level j over the immediate lower level. This improvement is a fraction of the accidents that no longer happen due to the current autonomous level j. The sum of all the improvements will be less than or equal to 1. From this we can see the TTC threshold for higher SAE levels is lower. Below is the table of the value of I_j for different SAE level j.

Based on the value of I_j the TTC threshold is calculated for every SAE level

Table 4.1. Improvement factors for SAE level

SAE level	Improvement Factor
0	0.0
1	0.35
2	0.15
3	0.15
4	0.2
5	0.05

4.3.4 Simulation run on VISSIM for different penetration of SAE levels

In order to create trajectory information of different SAE levels and also to make sure that the interactions between various SAE levels are also captured simulations are run for different penetration for each SAE level. The above SAE models are run across diverse road networks in order to capture driving behavior in different settings. The trajectory of the AVs are written in a TRJ file from VISSIM.

4.3.5 Conflict Analysis

Conflict Analysis is a methodology to identify risky maneuvers on roadways. It has been proved to be a reasonable substitute for accident data modeling. Surrogate safety methods have been used in the micro simulation context in many studies. [103] in his study used microsimulation to evaluate the safety levels at signalized intersections. He used TTC as the surrogate measure to evaluate the safety levels. [101] used TTC to predict crash risk using the conflict methodology in a microsimulation environment. [100] analyzed aggressive drivers in a micro simulation using a microsimulation approach. He modeled aggressive drivers by creating a class of vehicles which followed too closely or which traveled above the speed limit. He showed that for very less increase in mobility the safety measures dropped significantly due the presence of these aggressive drivers in traffic. There are multiple surrogate measures

Table 4.2. TTC Thresholds

	SAE 0	SAE 1	SAE 2	SAE 3	SAE 4	SAE 5
Low	6	4.2	3.5	2.8	2	1.5
Medium	4.5	3	2.4	2	1.6	1.2
High	2.5	1.8	1.5	1.2	0.9	0.7

of safety which have been created that include TTC, PET, MaxD, Max Delta S etc. Post encroachment time is the time taken by the follower vehicle to reach the same position as the leader vehicle. This has a slightly different value compared to TTC because TTC is a hypothesize value where as PET is what actually happens as the vehicle travels to it's successor's position. MaxD is another surrogate measure which provides the maximum deceleration of the follower vehicle in the conflict region. Max Delta S is surrogate measure which provides the maximum absolute speed difference between the follower and the leader vehicle. This measure captures the big speed differentials that occur many times in the case of accidents. We use the modified version of TTC as the conflict evaluation criteria, since it is the most commonly used measure to provide accurate measurement. We have used SSAM as the tool to do analysis in the conflicts framework methodology. SSAM is a powerful tool which has been developed by FHWA and has been used in multiple studies. It can process trajectory information from multiple leading microsimulation softwares in a very efficient manner. We use this tool to evaluate the various SAE levels vehicle trajectories and analyze the different conflict measures provided by the tool.

4.3.6 Trajectory analysis for various SAE levels

This TRJ file is provided as an input to the SSAM software which is a conflict analysis tool used for analyzing traffic conflicts. There are a few limitations of this tool. One of the limitation of this tool is that it does not differentiate the grade separation between roads which can result in multiple ghost conflicts. These conflicts need to be removed in order to identify the real conflicts that happen during the simulation. The SSAM software outputs different characteristics of each conflict situation which include TTC, PET, MAX D, DR, MAX Delta S etc. A lower value of TTC represents a higher probability of a conflict. TTC calculated for the conflicts do not account for the SAE type. Therefore the TTC values do not reflect the same severity level across SAE classes. Hence,there is a need to categorized these TTCs based on SAE specific thresholds calculated by the above formula.

This trajectory information is used as an input in SSAM which evaluates conflict probability based on the trajectory of vehicles. The software analyzes the trajectories and provides information on the severity of the conflicts the different vehicles were involved in.

4.3.7 Machine Learning Models

Data driven approach has been used in the context of risk identification on road networks. Here in this work we uniquely capture the benefit of conflict based safety analysis and the strength of advanced data driven predictive methodologies. This combination as far as we are aware has not been attempted before specially in the context of SAE classified AVs. The output from the previous step of trajectory analysis is used as the label of the vehicle which is classified either as no risk, low risk, medium risk and high risk depending upon the SAE specific TTC thresholds. This problem has been defined as a classification problem instead of a regression problem which also was a distinct possibility given that TTC is a continuous variable. However, SSAM evaluates the conflict measures only between certain ranges for TTC between 0 to 10. A more intuitive construction of the problem would be a multi-class classification problem. We evaluate 3 machine learning methods and compare the performance of these methods in the context of medium sized data. Even though VISSIM can provide trajectory information for vehicles beyond their own i.e for example the distance between the vehicle and its neighbors, the speed differential between the vehicle and its neighbors, the acceleration of the neighboring vehicles etc. But this kind of data may not be available in the context of AVs. Therefore, we restrict our input data to only the vehicle trajectory level information to represent real world situations of data availability more realistically. Therefore, the data information which is extracted from VISSIM as input to the machine learning models are the vehicle position, velocity, acceleration, distance traveled, time taken. We use trajectory information to create more than 50 features which is used for the machine learning purpose.

Problem Definition

Accident or traffic conflicts are rare events. For example- an accident occurs once in every million miles travelled. Similarly, conflicts are also very rarely observed. Therefore, the Y labels in our problem will mainly constitute of zeros which represent no conflict. The rest of the values 1, 2, 3 are very less in number. Therefore, we will have to use an anomaly detection framework in order to identify conflicts correctly. At the same time the purpose of identifying the risk level of vehicles is in the context of insurance pricing and therefore, identifications of zeros are also useful.

Data Description

The data set used for our analysis comprises of trajectory information of vehicles of different SAE types on a freeway interchange and a 3 by 3 signalized intersection. The below table gives the volume composition of the different SAE levels. For each network we have used the three types of volume composition data sets as given below.

Table 4.3. Volume Composition

Dataset type	SAE 0	SAE 1	SAE 2	SAE 3	SAE 4	SAE 5
1	16.66%	16.66%	16.66%	16.66%	16.66%	16.66%
2	4.75%	9.5%	14.25%	19%	23.75%	28.5%
3	28.5%	23.75%	19%	14.25%	9.5%	4.75%

The dataset type 1 constitutes of different SAE levels in equal proportion. The dataset type 2 has decreasing proportion as SAE level increases. The dataset type 3 has increasing proportion as the SAE level increases. Different volume compositions are used in order to make sure the driver behavior of each SAE level is captured especially since the TTC thresholds for the higher SAE levels is quite low.

Data Pre-processing

The data from VISSIM needs to be preprocessed before providing it as an input to the machine learning models. The granularity of the data is for every 0.1 sec. Following are the inputs used from VISSIM.

1. Velocity
2. Acceleration
3. Vehicle type
4. Lane change or not (1 or 0)
5. Position from the center of the lane: -ve is left of center and +ve is right of center
6. Current link
7. Current lane
8. X coordinate of the front of the vehicle
9. Y coordinate of the front of the vehicle

Many times as vehicles are generated by VISSIM, before it enters the network the vehicle level data associated with it are placeholders. Therefore, these data needs to be filtered so that this kind of information is removed from the original data set.

Feature Engineering

The preprocessed data as mentioned above is every 0.1 sec for every vehicle in the network. This data is used to create two types of features. The first kind is aggregate levels of features. For example - Distance travelled by the vehicle in a particular speed range or acceleration range. The other kind of features that are generated are for example - maximum speed, minimum speed, maximum acceleration, minimum acceleration, maximum jerk, minimum jerk etc. These two kind of features are created because both of them together are able to characterize driver behavior which can be analyzed in the machine learning data driven framework.

Model Selection

In our framework we have decided to choose 3 machine learning models in order to evaluate the above data set of various SAE level trajectory data. Below is a brief introduction to each of the methods.

1. Logistic Regression - Logistic regression is one of the most widely used machine learning techniques. In this study we use a multinomial logistic regression model for classification which is suited to the multiclass nature of the problem. The probability of each alternative is estimated by

$$Pr(Y_i = m) = \frac{e^{\beta_m . X_i}}{1 + \sum_{k=1}^{K} e^{\beta_k . X_i}} \tag{4.3}$$

   The parameters of the vector β_m are estimated using maximum a posteriori estimation. Since logistic regression is used quite commonly we are going to benchmark the performance of the other models against it.

2. XG Boost - Gradient boosting employs the methodology of sequential learning. It uses weak learners to iteratively optimize a loss function using the Gradient Decent Method. This method builds its learner and then computes the loss,

the difference between the prediction and the actual value. In the subsequent iterations, the learner improves over the previous loss level and hence improves. Extreme Gradient Boosting is known to perform very well with unbalanced datasets which is the nature of our dataset and hence a natural candidate for the analysis.

3. Neural Networks - As the third classifier we utilize a neural network with 3 hidden layers and ReLU activation function which is represented by $R(z) = max(0, z)$. The ReLU activation function is the currently one of the most accepted activation functions. Neural Networks have been highly successful in multiple ML tasks and have been shown to be superior to other classifiers while performing classification tasks.

The fourth model is an ensemble model which combines the previous 3 models via the stacking technique using logistic regression as the meta classifier. Stacking is an ensemble method, where a model is built using the output of the base models as inputs. These new inputs are used to create a new set of predictions.

Sampling Methodology

When machine learning methods are used for unbalanced data sets, they can become very biased to the majority class in order to increase over all accuracy. In order to decrease the bias we have used two methods. The first method is applied while dividing the data set into testing and training data. We used stratified sampling technique in order to make sure that the minority classes are presence in both testing and training data. The second method used in order to improve the prediction accuracy of skewed dependent variables we use under sampling of majority class. This is done in order to reduce the bias of the machine learning models while predicting the majority class.

4.4 Results And Analysis

In order to analyze the predictability of the above discussed anomaly detection machine learning algorithms we use two types of networks. The first network is the I65 and I465 freeway interchange. This interchange is one of the main interchanges near Indianapolis with a lot of merging and diverging sections. This gives us ample opportunity to record conflicts that may arise due to the traffic comprising of various SAE level vehicles. The 3 vehicle compositions used to generate the trajectory information is as mentioned in Table . The second network used is a 3 by 3 signalized grid which represents an arterial setup. This setup provides for significant number of stop and go behavior which result in conflict and hence is useful to analyze. Below are the figures for the two networks.

Table 4.4. Volume Composition

Dataset type	SAE 0	SAE 1	SAE 2	SAE 3	SAE 4	SAE 5
1	16.66%	16.66%	16.66%	16.66%	16.66%	16.66%
2	4.75%	9.5%	14.25%	19%	23.75%	28.5%
3	28.5%	23.75%	19%	14.25%	9.5%	4.75%

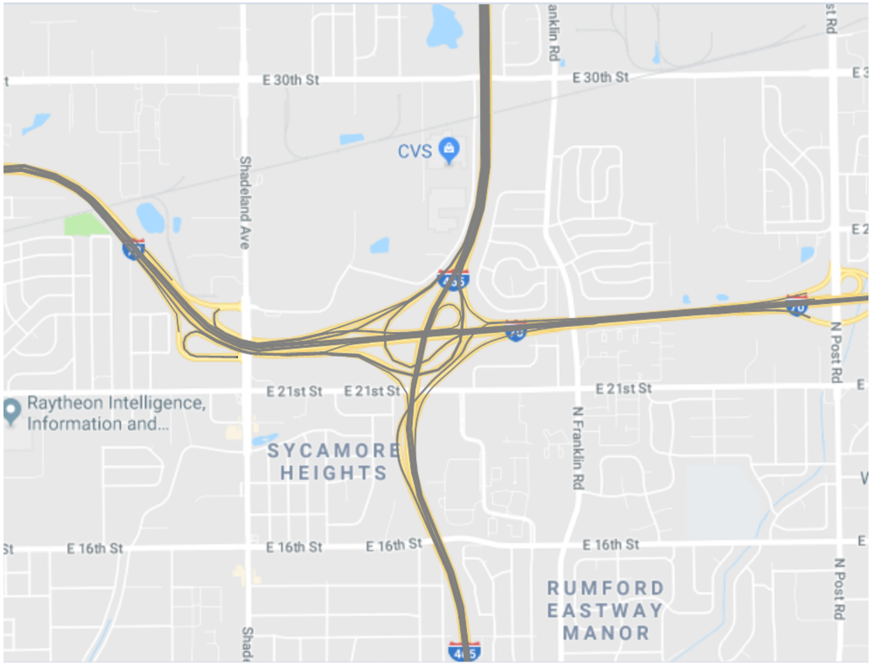

Figure 4.2. Freeway interchange

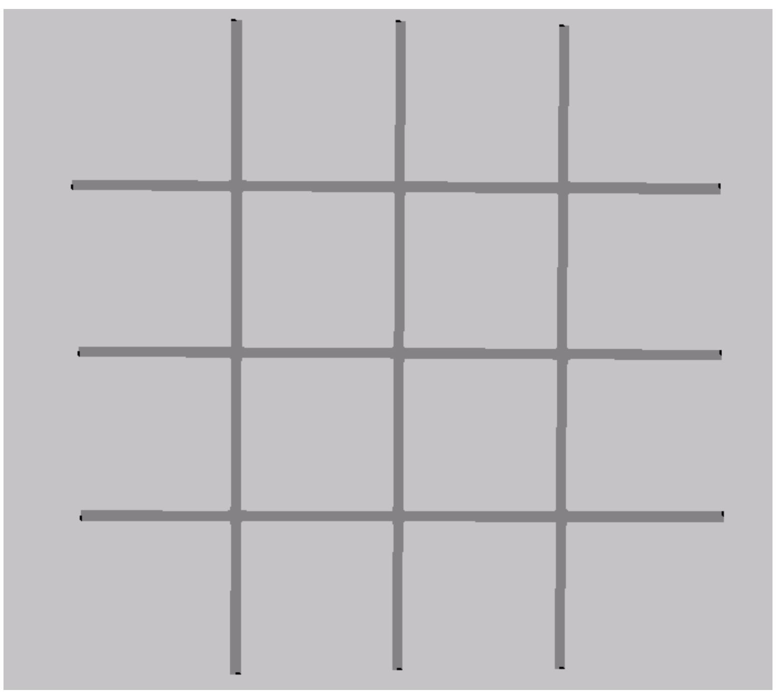

Figure 4.3. 3 by 3 signalized grid

Network 1 is I65 and I465 freeway interchange, near Indianapolis. In this particular network there are 5 merging points and 6 diverging sections. The traffic volume on the freeway is assumed to be 1,000 vehicles per lane per hour. In total the entire network has 20,700 vehicles per hour. Network 2 has 9 signalized intersection with a distance of 0.33 miles between each signal. This represents the downtown grid observed in multiple cities. We attempt to analyze these two networks in the study.

The measures used to analyze the performance of given models are recall and F1 score. This is done because as discussed earlier the dataset is highly imbalanced and the main interest of this study is to identify the anomalies. Instead of checking just for accuracy which can give a very biased opinion on the performance of the model, we need to look at more suitable measures which will reflect the performance of the model accounting for the special nature of the problem. Recall is used to identify how well the model is able to identify the positively labeled data points. In order to compare the performance of the model on the original dataset vs. the dataset with under-sampled majority class, we train the model on these five datasets and compare their recall and F1 score. These five datasets include original, 10%,40%,60%, and 90% under-sampled majority class datasets. An illustrative confusion matrix is presented for dataset 1 of network 1 in Table 4.5 - Table 4.14. From the analysis of the confusion matrices for dataset 1 of network 1, we see that the accuracy of all the four models is higher for the four undersampled sets. This is because the models have been as highly biased in the case where undersampling is done as compared to the case in which the entire dataset is used to train the models.

The results from the machine learning models on the simulated datasets has been presented in the figures below. These models were trained on the original datasets and undersampled datasets as well. The model performance has been evaluated using the confusion matrix, recall, F1 Score. The recall and the F1 score for the 3 datasets for different levels of undersampling of the majority class, are shown in Figure 4.4 - 4.9. We see that the stacking technique clearly outperforms all the models irrespective of the extent of sampling or volume composition for both the networks. The technique shows strong level of robustness across different scenarios. This is due to the fact that the ensemble method is able to avoid overfitting as compared to the base models by blending of the decision boundaries. The base models are able to learn different aspects of the problem with differential abilities. Stacking combines these capabilities and creates a robust model with higher accuracy. At the same time neural networks and XG Boost perform fairly well. Logistic regression performs the worst in all scenarios.

LR				
	0	1	2	3
0	10475	121	53	27
1	2	0	0	0
2	10	0	0	0
3	5	0	0	0

XGB				
	0	1	2	3
0	10467	118	51	26
1	15	1	0	0
2	7	1	1	1
3	3	1	1	0

NN				
	0	1	2	3
0	10469	117	51	26
1	10	2	1	0
2	12	1	0	0
3	1	1	1	0

S				
	0	1	2	3
0	10470	117	51	27
1	5	2	1	0
2	17	1	0	0
3	0	1	1	0

Table 4.5. Confusion matrix for original Dataset 1 of Network 1

LR				
	0	1	2	3
0	9202	108	47	24
1	18	8	2	2
2	9	4	2	1
3	4	1	1	1

XGB				
	0	1	2	3
0	9211	100	45	20
1	13	16	3	3
2	6	3	4	0
3	3	0	1	3

NN				
	0	1	2	3
0	9215	97	42	19
1	8	18	1	3
2	8	3	5	1
3	1	1	1	5

S				
	0	1	2	3
0	9220	94	43	19
1	5	19	1	1
2	7	2	6	3
3	2	4	1	4

Table 4.6. Confusion matrix for 10% undersampled Dataset 1 of Network 1

LR				
	0	1	2	3
0	6073	100	44	22
1	12	12	4	0
2	6	8	4	1
3	3	1	0	3

XGB				
	0	1	2	3
0	6079	106	40	16
1	610	10	4	2
2	3	3	7	1
3	2	0	1	8

NN				
	0	1	2	3
0	6083	92	40	15
1	4	22	1	2
2	6	4	8	2
3	0	1	3	7

S				
	0	1	2	3
0	6086	88	38	14
1	5	23	2	2
2	3	4	11	3
3	0	2	0	8

Table 4.7. Confusion matrix for 40% undersampled Dataset 1 of Network 1

LR				
	0	1	2	3
0	3525	85	37	19
1	5	25	5	1
2	3	10	10	0
3	2	1	0	6

XGB				
	0	1	2	3
0	3528	72	30	14
1	5	39	5	3
2	3	8	16	1
3	1	0	1	9

NN				
	0	1	2	3
0	3525	71	31	12
1	5	42	1	1
2	2	5	17	3
3	2	2	3	9

S				
	0	1	2	3
0	3530	67	20	11
1	5	50	3	3
2	0	6	28	3
3	0	1	0	10

Table 4.8. Confusion matrix for 60% undersampled Dataset 1 of Network 1

LR				
	0	1	2	3
0	952	70	22	12
1	1	40	7	2
2	1	8	23	0
3	0	2	0	12

XGB				
	0	1	2	3
0	953	55	10	10
1	1	56	7	3
2	1	4	34	1
3	0	4	1	13

NN				
	0	1	2	3
0	952	54	10	9
1	1	58	2	1
2	1	6	38	3
3	1	2	2	12

S				
	0	1	2	3
0	953	59	9	5
1	1	50	3	3
2	0	7	39	3
3	0	1	0	15

Table 4.9. Confusion matrix for 90% undersampled Dataset 1 of Network 1

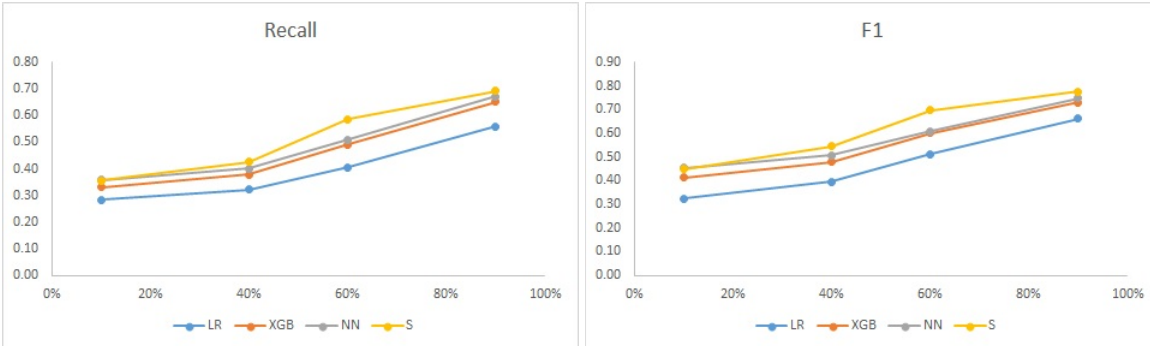

Figure 4.4. Network 1 Dataset 1

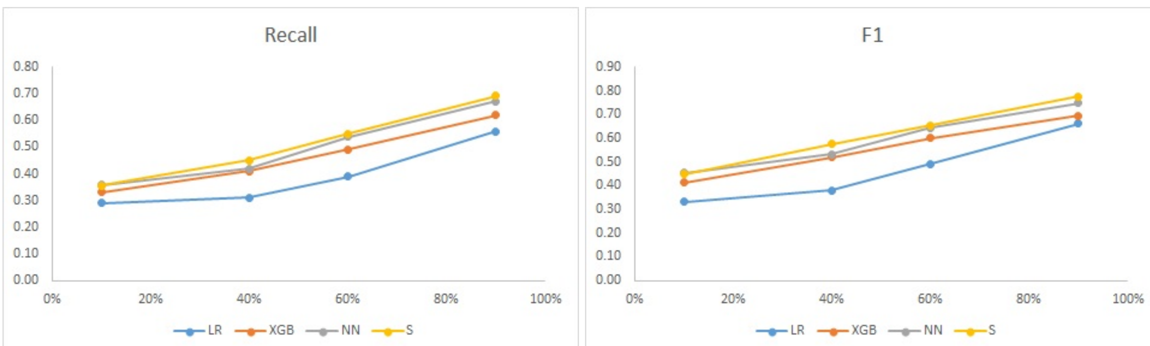

Figure 4.5. Network 1 Dataset 2

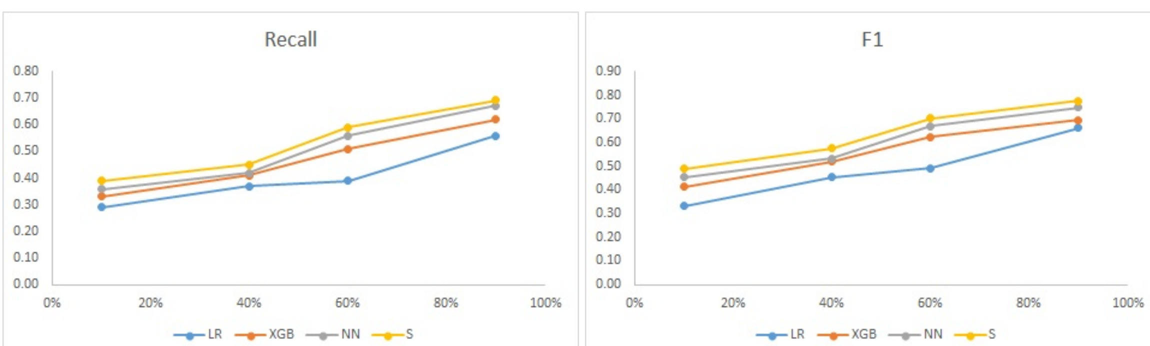

Figure 4.6. Network 1 Dataset 3

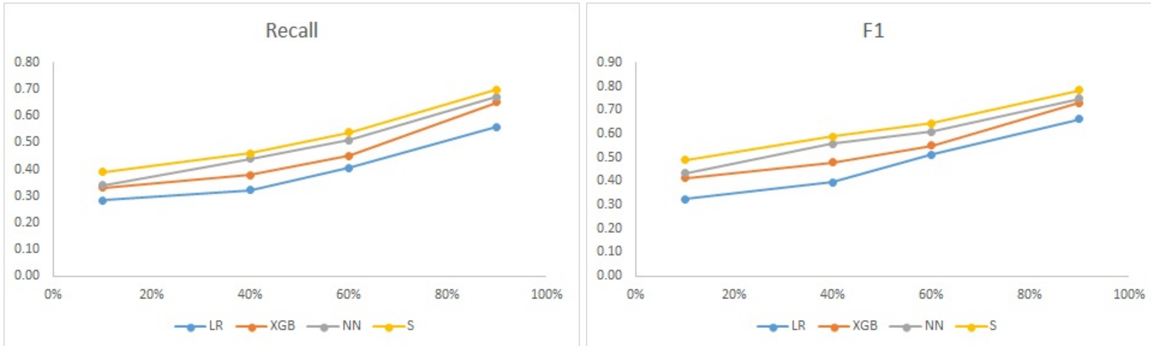

Figure 4.7. Network 2 Dataset 1

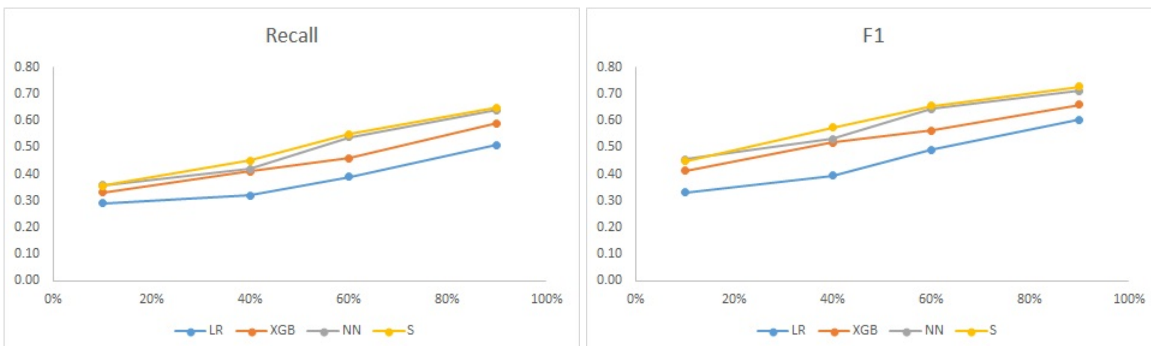

Figure 4.8. Network 2 Dataset 2

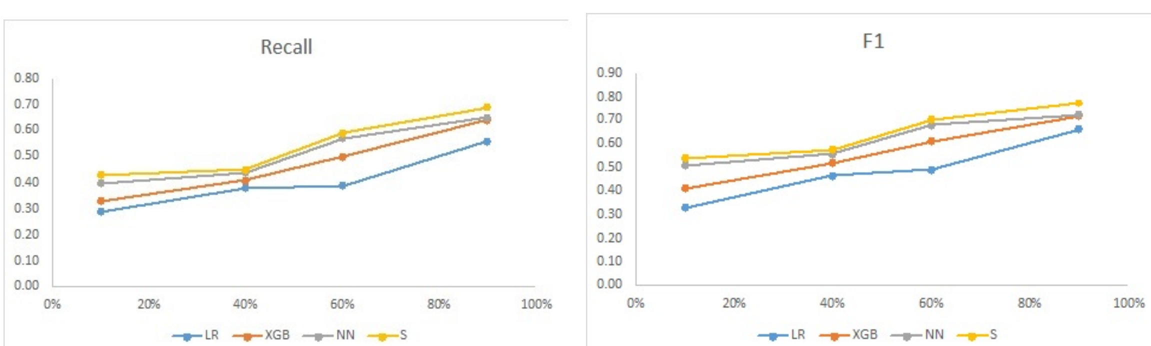

Figure 4.9. Network 2 Dataset 3

4.4.1 Conclusions

This work makes a significant contribution in the modeling of risk assessment of various SAE levels. The conflict analysis framework has been redefined in the AV context for different SAE levels. The newly defined thresholds attempt to reflect the surrogate safety measure of time to conflict in the autonomous setting. We attempt to identify using our proprietary SAE models to generate AV trajectory. This trajectory is input into the SSAM software developed by FHWA. The software identifies conflicts between vehicles based on TTC thresholds among others. The TTC output of SSAM are then compared against the thresholds proposed to identify the risk levels of the vehicles. Due to the stochastic nature of the SAE levels driving behavior, a very small percentage of them behave in the risky manner. Using machine learning models trained on the created datasets a prediction methodology has been attempted. We looked at four machine learning models, logistic regression, XG Boost, neural networks and a stacked ensemble of these 3 models. Logistic regression performed the worst among all 4 models in the case of both the networks. XG Boost performs relatively better than Logistic Regression. Neural Networks consistently has higher performance in both the network settings as compared to XG Boost and Logistic Regression. The stacked ensemble smoothens out the prediction of the 3 base models and provides higher prediction accuracy in terms of recall and F1 score. therefore, we recommend a stacked ensemble technique in order to identify risky behavior in the context of AVs.

This work will be an asset for practitioners, policymakers and researchers to perform safety analysis and risk assessment as AV penetration increases in the future. The model can accommodate different mixes of traffic, and therefore the work can also be used to test the impact of various permutations of SAE level penetrations. With this work as a foundation, extensions of future work can be in multiple areas. Research divisions at insurance firms can assess the risk levels of of autonomous vehicles by calibrating this model with the ground data.

5. CONCLUSIONS

5.1 Summary

The landscape analysis of AVs via the 28 interviews and 33 surveys conducted, revealed various critical key conclusions. It is evident that the market introduction of autonomous vehicles (AVs) will take two directions. Vehicles with a low level of autonomy will be available for retail purchase, whereas Original Equipment Manufacturers (OEMs) and transportation service providers will deploy highly automated vehicles via Transportation-as-a-service model. Furthermore, CAVs will take an evolutionary, path of development. In addition, the deployment of robo taxis will be done on a city-by-city basis, because Society of Automotive Engineers (SAE) level 4 vehicles that would be employed will have an operational design domain restricted by geo-fencing. Also, current partnerships between CAV stakeholders are extremely weak. Strengthening these offers the potential to guide CAV evolution in a more efficient and constructive manner. Moreover, the large scale at which CAV technology will be deployed leaves it vulnerable to issues that will cause a poor consumer willingness to purchase, high prices, and OEMs being left behind in a disruptive market. This must be accounted for in future deployment decisions Lastly, the stakeholders have falling short of building transformative collaborations and disagree on key CAV matters, such as the need for connectivity. A consensus must be built to facilitate efficient CAV evolution in the future.

The fact that AVs would be very different in their performance based on the level of autonomy led us to study the various impacts that they will have on road traffic. The mobility analysis indicates that mobility in SAE level 1 always exceeds that of SAE level 0, because the former has a consistently higher acceleration for given conditions. SAE level 2 provides more lateral stability and therefore less implied accidents than level 1 or 0 due to lower lateral deviations. For level 3, the key consideration is to model the transition between human and system control. In SAE level 4 we model the operation of autonomous vehicles in Operational Design Domain (ODD) and transition to minimal risk conditions outside ODD. SAE level 5 overcomes the impact of these transitions and hence has a better mobility than the lower SAE levels. We also performed penetration studies for various SAE mixes in the road traffic and analyzed their mobility impacts. The models can help policymakers to understand the impact of autonomous vehicles on mobility and guide them in making critical policy decisions.

The safety aspect of AVs has not be studied earlier at the SAE level. In this study we create a framework which can be used to evaluate risk levels for various SAE classes. Firstly based on previous data on manner of collision we define different TTC thresholds for the different risk class for each SAE level. Using our in house built models which mimic the different levels of autonomy we run simulations to capture the trajectory of AVs. Using this trajectory data and threshold levels we identify the riskiness of the all vehicles across each SAE level. We used this data as our input we build a prediction model which identifies riskiness in SAE vehicles based on their trajectory data. We used machine learning models namely logisitc regression, neural networks, XGBoost and an ensemble model which stacks the three machine learning algorithms to attempt to identify the risk level of vehicles. In order to do that we utilize the anomaly framework due to the sparseness of the data which reflects real life settings. The majority class is undersampled in order to reduce the bias in the model and to improve the prediction accuracy for the risk labels. We created 3 datasets for 2 networks. The first network was the I-70 and I-465 intersection and the second network was a 3 by 3 grid . These two networks were chosen in order to test the effectiveness of the prediction model in diverse networks and different volume compositions. We found the ensemble method which combines the prediction capcility of the three base models performs better than the rest. In a data scarce environment this model which combines conflict analysis framework and microsimulation environment can be very valuable.

5.2 Limitations

The main limitation this work faces is due to the challenge it faces in terms of validating the results. The modeling of AVs is based on sound assumptions and the results therefore reflect the reasonable foundations of the model. At the same time the work will need validation in terms of calibration of the parameters used for the mobility and safety analysis. As data will become more available in the future we expect to validate and calibrate our models.

The machine learning models we have built are based on the simulated trajectories from the AVs. Again, the fact the data is simulated can raise a few questions but currently not all SAE levels are even on roads which limits the extent to which they can be currently validated.

5.3 Future work

A series of future works can be an extensions of this work. Some of them are as below.

1. The SAE modeling can be built into a tool which can be used by OEMs, state agencies and transportation consulting firms.

2. The SAE modeling be made more detailed by adding more automated functionalities, like traffic jam assist, emergency braking etc to the model and testing their impacts.

3. The models can be tested for different traffic conditions to look at the impacts in more diverse scenarios

4. The impact on SAE 4 level vehicles on travel demand will be a useful research problem.

5. Driver risk prediction tool can be used in future models which predict route risk as a combination of driver risk and other external factors.

6. Further work can be done on identification and analysis of issues and the critical challenges which will dictate and affect the DSRC and 5G paths.

7. As the data for various SAE level vehicles become more available, models which combine functional as well as data driven models will go a long way in creating safer as well as efficient autonomous vehicles

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