Title

Scenario-Based Drive Cycle Analysis Framework for Zero Emission Vehicles with Cooperative Driving Automation

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Scenario-Based Drive Cycle Analysis Framework for Zero Emission Vehicles with Cooperative Driving Automation

THESIS

Submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Mechanical and Aerospace Engineering

By

Eric Fong

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Professor G. Scott Samuelsen, Chair

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2023

Dedication

To my family for believing in and supporting me throughout all challenges.

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List of Acronyms

ABS	Anti-lock Braking System
ACC	Adaptive Cruise Control
ADAS	Advanced Driver-Assistance Systems
AEB	Automatic Emergency Braking
AI	Artificial Intelligence
AV	Autonomous Vehicle
BEV	Battery Electric Vehicle
CDA	Cooperative Driving Automation
CFD	Computational Fluid Dynamics
C.F.R.	Code of Federal Regulations
DARPA	Defense Advanced Research Projects Agency
DSRC	Dedicated Short-Range Communication
EIA	Energy Information Administration
EPA	Environmental Protection Agency
FASTSim	Future Automotive Systems Technology Simulator
FCEV	Fuel Cell Electric Vehicle
FMVSS	Federal Motor Vehicle Safety Standards
FTP	Federal Test Procedure
HWFET	Highway Fuel Economy Driving Schedule
ICE	Internal Combustion Engine
ICV	Internal Combustion Vehicle

ITS	Intelligent Transportation Systems
LKA	Lane Keep Assist
M2M	Machine-to-Machine
NREL	National Renewable Energy Laboratory
PEM	Proton Exchange Membrane
SAE	Society of Automotive Engineers
SAV	Shared Use Autonomous Vehicle
UDDS	Urban Dynamometer Driving Schedule
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
VMT	Vehicle Miles Traveled
ZEV	Zero-Emission Vehicle

Abstract of the Thesis

Scenario-Based Drive Cycle Analysis Framework for Zero Emission Vehicles with Cooperative Driving Automation

By

Eric Fong

Master of Science in Mechanical and Aerospace Engineering

University of California, Irvine, 2023

Professor G. Scott Samuelsen, Chair

The next evolution of vehicle mobility is anticipated to include, along with zero-emission vehicles (ZEVs), the introduction of cooperative driving automation (CDA) encompassing both autonomous vehicles (AV) and connected infrastructure. CDA offers enhanced comfort and safety for the passengers and, potentially, an improvement in fuel economy. For example, on urban roadways, communication to the vehicle from smart traffic signals can adjust and smooth vehicle speed and reduce fuel use. Additionally, communication between vehicles allows for group coordination that can improve aerodynamics and reduce fuel consumption. This thesis explores the role of the vehicle drivetrain in responding to CDA communication. With the growing population of zero-emission battery electric vehicles (BEV) and hydrogen fuel cell electric vehicles (FCEV), the focus of the thesis is directed to electric drivetrains with the goal to project the fuel savings from connected and autonomous mobility.

The results reveal that the addition of CDA to ZEVs result in an increase in city fuel economy of 6% to 12% with a infrastructure to vehicle connectivity range not exceeding 250 meters to 450 meters respectively. As the connectivity range increases above 350 meters, the fuel efficiency gains diminish. The addition of CDA increases highway fuel economy by 6% to 32%

due to reduced drag from vehicle platoons. Future vehicle technology improvements that increase the efficiency of individual powertrain components are found to decrease the amount of fuel economy improvements when adding CDA. Resulting fuel economy improvements from equipping vehicles with CDA are projected to reduce the fuel cost to consumers by 6%.

1. Introduction

1.1 Overview

The state of mobility is ever changing. In the past, technological advancements in powertrain design and safety features have gradually improved vehicle efficiency and safety. For example, hybrid-electric powertrains are capable of increasing fuel economy by 40% over traditional internal combustion engines (ICEs) [1]. Additionally, the requirement for seat belt usage has shown that these devices are effective by reducing the rate of injuries from traffic related accidents [2]. Today, new advances in vehicle propulsion and driver assistance systems are being developed to further improve automobile efficiency and safety.

Currently, fossil fuels are the primary source of energy for vehicle propulsion. Burning fossil fuels for ICEs and electricity generation emit harmful pollutant emissions and greenhouse gases into the atmosphere. While advances in powertrain technology have increased the efficiency of internal combustion vehicles (ICVs), unsustainable amounts of greenhouse gases continue to be emitted by them. In response to climate change caused primarily by greenhouse gases, several US state governments have mandated the adoption of zero-emission vehicles (ZEVs). California has led the way by developing regulations that will require all new passenger vehicles be zero-emission by 2035 [3]. Battery electric vehicles (BEVs) and hydrogen fuel cell electric vehicles (FCEVs) are the main types of ZEVs being developed and marketed by automobile manufacturers. With the increased adoption of renewable wind, solar, and hydro electricity generation, the production of alternative fuels is increasingly becoming emission free.

In the past, passive safety features, such as airbags and seatbelts, have helped to save lives in the event of an accident. Because passive safety features activate during an accident, there is still a chance for occupants to sustain an injury or death. In contrast, active safety features work to prevent accidents from occurring. Currently, automakers are marketing advanced driver-assistance systems (ADAS), such as automatic braking, lane keep assist, and adaptive cruise control, as tools to protect drivers from hazards on the road. These systems process data from a variety of sensors (e.g., cameras, radar, and lidar) to automatically alter vehicle dynamics through algorithms and actuators.

To further reduce the human factor in driving, various companies are applying ADAS to enable a future of autonomous vehicles (AVs). The Society of Automotive Engineers (SAE) outlines six levels of vehicle autonomy in standard J3016, listed in Table 1. At automation level two and below, humans are required to operate the vehicle at all times. At automation level three and above, the system operates the vehicle with possible or no human intervention. Automobiles marketed to the public today have at most partial driving automation (level 2). Both academia and industry are conducting research and development of vehicles of with automation levels three and above.

Table 1: SAE Levels of Driving Automation, from [4]

SAE Level	Name	Definition
0	No driving automation	Human driver performs all driving tasks
1	Driver assistance	ADAS system performs either steering or acceleration while human driver performs remaining driving tasks
2	Partial driving automation	ADAS system performs both steering and acceleration with human driver supervision
3	Conditional driving automation	ADAS system performs all driving tasks with human driver override
4	High driving automation	ADAS system performs all driving tasks with no expectation of human driver override
5	Full driving automation	ADAS system performs all driving tasks without human driver override

Another new advancement in active safety features is the addition of connected vehicles and infrastructure. These vehicles and infrastructure can connect using dedicated short-range communication (DSRC) to create a wireless communication grid. The combination of both autonomous driving and connected mobility is known as cooperative driving automation (CDA) [5]. Machine-to-machine (M2M) communication can make vehicles safer by allowing them to quickly receive and react to information about upcoming stops or hazards. Another effect of CDA and its early hazard recognition is the possible impact on fuel consumption.

Since 1958, the Automobile Information Disclosure Act of 1958 has required that all new cars sold in the United States have a sticker, called the Monroney sticker, posted on the window that lists vehicle specifications [6]. An example of a current Monroney sticker for an electric vehicle is shown in Figure 1. Over the years, additional information, such as fuel economy, has been added to these stickers. The information these stickers provide could heavily influence the decisions buyers make for their new car purchase. With ZEVs and CDA being the next frontier of vehicle technology, it is important that the Monroney sticker accurately captures their effects on fuel economy

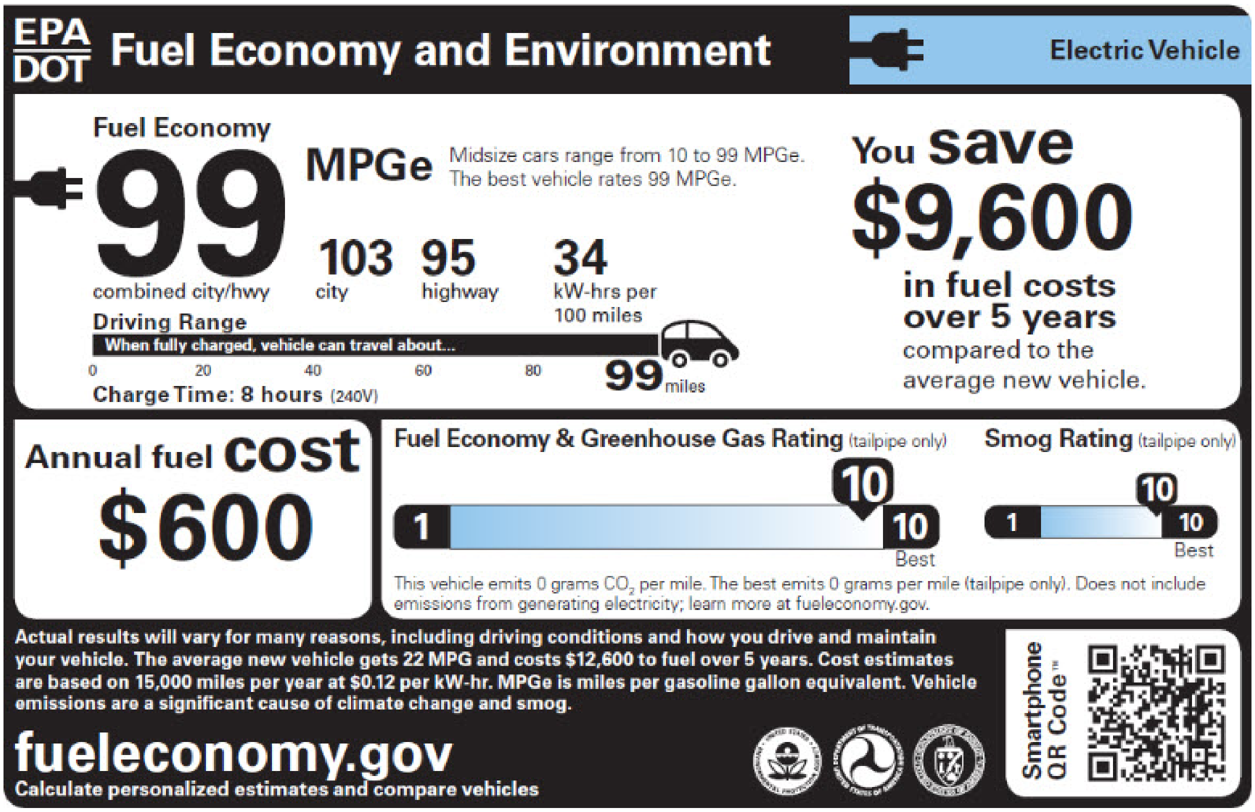

Figure 1. Monroney Sticker for an Electric Vehicle, from [7]

This thesis addresses this gap by using computer simulation to determine the potential fuel efficiency gains from ZEVs with CDA. Real-world scenarios such as traffic light changes and accident-avoidance situations are important to study because they highlight situations where CDA could have potential energy savings. However, the study of individual traffic scenarios will not accurately represent the comprehensive energy benefit of CDA. As a result, the focus of this study will be on scenario-based drive cycle analysis. These drive cycles will represent the dynamics of a typical trip by a vehicle equipped with CDA. The potential fuel efficiency gains of ZEVs from CDA are analyzed by comparing the fuel consumption of new CDA drive cycles to existing drive cycles used by the United States Environmental Protection Agency (EPA).

1.2 Goal

The goal of this research is to:

- Develop and apply a powertrain analysis methodology that incorporates CDA impacts on drive cycles and ZEV powertrain characteristics to evaluate fuel use impacts from a transition to connected and autonomous mobility.

1.3 Objectives

The following objectives were established to achieve the goal of this research:

1. Analyze and select CDA scenarios and a powertrain simulation model.
2. Develop a methodology that incorporates the powertrain model to address CDA fuel use impacts
3. Test CDA drive cycles using the selected powertrain model.
4. Apply the methodology to analyze and compare powertrain models on fuel use with and without CDA.

2. Background

2.1 Advanced Driver Assistance Systems

Human operation of motor vehicles is one of the most dangerous modes of transportation. Despite improvements in automobile safety, 95% of the risk of transportation fatality occurs due to highway crashes [8]. In 2020, nearly 39,000 people in the United States died in motor vehicle accidents, causing an economic cost of $242 billion [9]. A study of automobile road safety in 1977 by the Institute for Research in Public Safety found that human error was a probable cause for 92% of all vehicle accidents [10]. For younger individuals, drug and alcohol use, excessive speed, and mobile phone use were frequent causes of accidents, while physical conditions, such as poor eyesight and slow reaction times, were associated with accidents involving older individuals [11]. Teenage drivers have a fatal crash rate per mile driven nearly three times as much as for drivers aged 20 and older [12].

In recent years, the development of vehicle safety features has shifted from protecting vehicle occupants from injury to preventing vehicle accidents from occurring in the first place [13]. The introduction of ADAS to vehicles is aimed at reducing instances of human error that could cause vehicle accidents. Sensors that comprise ADAS can be sorted into two types: proprioceptive and exteroceptive. Proprioceptive sensors analyze vehicle behavior to react to possible dangers, while exteroceptive sensors analyze spatial data to predict possible dangers [14]. The first ADAS introduced to consumer vehicles were anti-lock braking systems (ABS) in the late 1970s [15]. These proprioceptive sensors detect each wheel's speed to determine a proper braking pressure that prevents wheel lockup and maintains traction. Driver assistance systems that have proven to increase vehicle safety eventually become mandated to be standard in all new motor vehicles. A 2004 study from the Monash University Research Centre found that ABS could reduce the risk of multiple vehicle accidents by 18% [16]. ABS, in conjunction with electronic stability control systems, became standard on all motor vehicles in the United States in 2011 with the Federal Motor Vehicle Safety Standards (FMVSS) 126 [17].

The spatial sensing ability of exteroceptive sensors is the backbone of modern driver assistance systems. By allowing vehicles to sense their surroundings, exteroceptive sensors enable ADAS that can react to dangers on the road. The main exteroceptive sensors used today are radar, camera, and lidar. Radar and lidar detect objects by measuring propagation time of reflected electromagnetic radio waves or laser beams, respectively, while cameras capture optical images of the surroundings [18]. The weaknesses of each type of sensor can be mitigated by combining sensing capabilities into sensor fusion [19]. Analog Devices lists the sensing capabilities for radar, lidar, and camera, as shown in Figure 2.

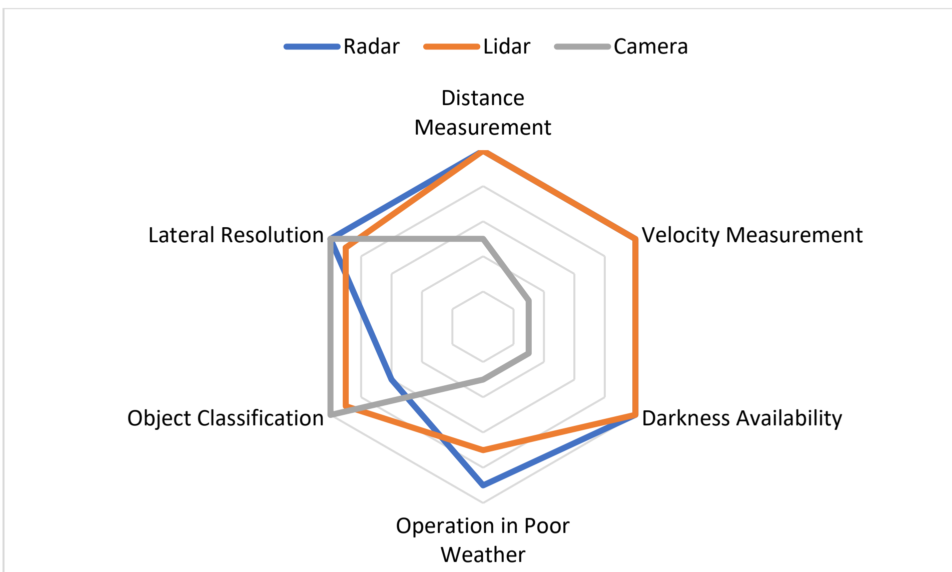

Figure 2. Sensing Capabilities of Radar, Lidar, and Camera, from [20]

Some of the modern ADAS systems that automobile manufacturers are offering include Adaptive Cruise Control (ACC), Automatic Emergency Braking (AEB), and Lane Keep Assist (LKA). ACC senses leading vehicles and automatically adjusts speed to maintain a safe following distance, as shown in Figure 3 [21]. AEB senses objects in front of the vehicle and automatically stops it if an imminent collision is detected, as shown in Figure 4 [22]. LKA determines if the vehicle is drifting from its lane and automatically provides steering support to prevent it from unintentionally leaving its lane, as shown in Figure 5 [23]. Each of these systems are at SAE Level 1 of automation, but the combination of multiple systems, e.g., ACC and LKA, qualifies as SAE Level 2 automation [24]. Many automakers are currently offering vehicles with Level 2 automation, such as Tesla's Autopilot system.

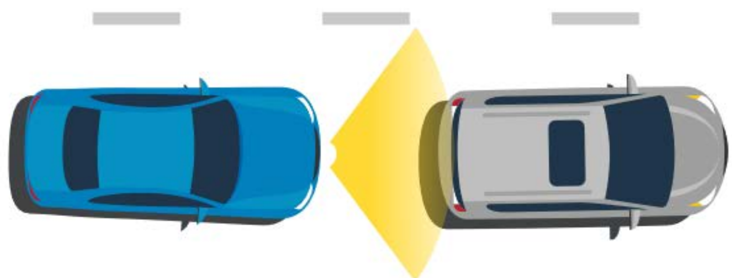

Figure 3. Adaptive Cruise Control, from [25]

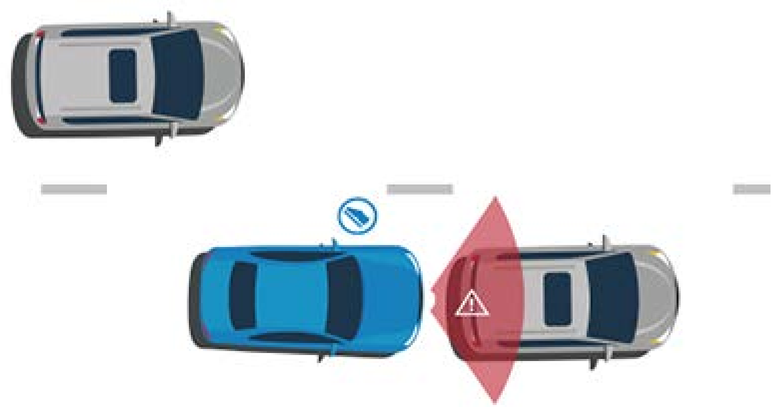

Figure 4. Automatic Emergency Braking, from [25]

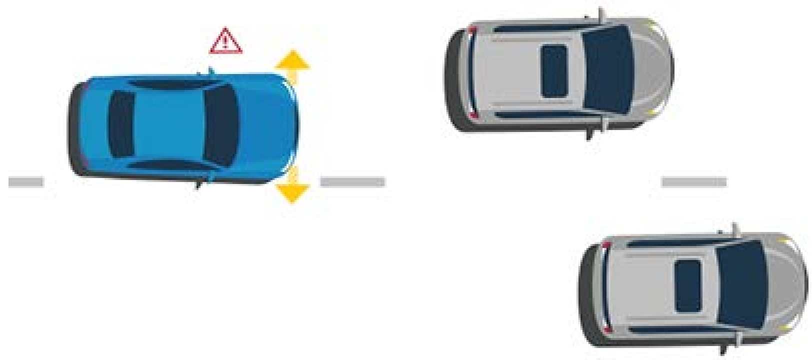

Figure 5. Lane Keep Assist, from [25]

2.1.1 Autonomous Vehicles

Autonomous vehicles utilize exteroceptive sensors to provide spatial information to a computer that can operate the vehicle with limited human interaction. Sensor fusion of radars, lidars, and cameras allow the vehicle to visualize its location and surroundings, while artificial intelligence (AI) software simulates human perception and decision-making tasks to operate steering and braking [26]. The combination of sensor fusion and AI can perform all driving tasks, corresponding to SAE automation Level 3 and above. At these automation levels, vehicles qualify as being autonomous.

The concept of autonomous vehicles has existed for over 100 years. Early ideas regarding AVs began in 1918; worldwide research and development programs on fleet platooning and video image processing occurred throughout the twentieth century [27]. Research activity on AVs intensified after Defense Advanced Research Projects Agency (DARPA), under the United States Department of Defense, created the Grand Challenges Program in 2004 to build AVs capable of traversing rugged desert terrain [27]. While no team could complete the 142-mile course in 2004, five teams were able to finish the race in 2005. Building on this success, DARPA’s 2007 Urban Challenge program had six teams successfully build AVs that could navigate city environments while following traffic laws [28]. Various groups in academia and industry have continued research and development of AVs with the hope of bringing this technology to the market. Various governments throughout the world are currently allowing autonomous systems to operate on city streets. As of 2021, California has permitted 48 companies to test AVs with a driver and seven companies without a driver on public roads [29]. Additionally, three companies have been allowed to deploy AVs for public use in California [29].

The deployment of AVs is projected to have major impacts on society. Because human error is the leading cause of vehicular accidents, implementing AVs could reduce crash and injury rates by 50% with only 10% market penetration; 90% market penetration could reduce crash and injury rates by 90% [30]. Robot drivers, along with lower rates of vehicle accidents, can increase traffic flow. It is estimated that freeway congestion will decrease by 15% with only 10% market penetration; 90% market penetration could reduce traffic congestion by 60% [30]. Increasing traffic flow could lead to an increase in fuel economy by eliminating stop-and-go traffic and decreasing travel times. At only 10% market share, AVs are projected to prevent 1100 deaths and save drivers $6 billion in economic costs while a 90% market share could prevent 21,700 deaths and save $110 billion in economic costs [30].

Additionally, AVs could change the way people and companies utilize transportation. By making vehicles easier to use, it is projected that the adoption of AVs would increase total vehicle miles traveled (VMT) and decrease use of public transportation [31]. On the other hand, autonomous technology could make commercial shared use AVs (SAVs) popular: a survey in metropolitan Brisbane, Australia found that 44% of people were willing to use SAVs for 50% of their trips [32]. The introduction and adoption of SAVs could decrease the need for personal vehicles. Furthermore, the developing automation from heavy duty vehicles could reduce costs by increasing operational efficiency, decreasing labor needs, and reducing fuel use from vehicle fleet platooning [33].

Many challenges must be overcome before AVs can be introduced and adopted by our society. Ethical concerns on decision making, liability, and privacy must be answered before AVs can be successfully deployed to the public. The first ethical concern about AVs relates to the issue known as the trolley problem, which involves choosing between two unfavorable scenarios. For AVs, this problem asks if the safety of the passengers should be prioritized over the safety of the public. To solve this, AI systems must perform quick cost-benefit analysis of the risk for each maneuver and act on the scenarios that give the highest level of confidence for success [34]. In the case of an accident involving an AV, the question of determining the responsible party arises. The government of the United Kingdom has plans to create a Code of Practice to determine how to allocate criminal and civil liability between AV drivers and AV manufacturers [35]. Another issue for AVs involves privacy concerns. Self-driving vehicles will collect large amounts of data on not only its surroundings, but also on how a person uses the vehicle. While the state of California already requires AVs to preserve data of the 30 seconds before a crash, no legislation in the U.S. exists on how user data created by an AV is collected, used, and distributed [35]. Without regulation addressing the ownership and use of AV information, privacy concerns could hinder adoption of autonomous technology.

Another barrier for the widespread adoption of autonomous technology is the high capital cost. In 2015, a single AV module for Google cost $80,000, which is out of reach for most consumers [36]. The pricing of AV technology is a major issue for consumers: 37% of people would be interested in purchasing a personal AV as their next vehicle if the price is comparable to conventional vehicles [36]. Another route for AV adoption would be the creation of SAV fleets. By having private companies cover the upfront cost of AVs, consumers would be able to utilize autonomous technology and only pay the price of SAV rental. A study from Switzerland found that while short term costs favored SAVs, the overall long-term costs for personal and shared AVs will be similar [37]. This suggests that the future of vehicle mobility will entail both shared-use fleets and private vehicles.

2.1.2 Connected Vehicles and Infrastructure

An emerging topic in the area of intelligent transportation systems (ITS) is the addition of connected vehicles and infrastructure. CDA improves AVs by adding vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. SAE standard J3216 defines CDA as having four classes of cooperation, as shown in Table 2. In status-sharing cooperation, information about current traffic conditions is shared between vehicles and infrastructure. Intent-sharing cooperation provides information about future actions the sender will perform. CDA devices that perform agreement-seeking cooperation work together to influence planning of a dynamic driving task. Prescriptive cooperation informs other CDA devices on what actions it should take. The M2M communication of CDA collects and shares valuable information such as road conditions, signal phases, traffic hazards, and emergency responses between vehicles and infrastructure.

Table 2. Classes of Cooperative Driving Automation, from [5]

Class	**Name**	**Description**
Class A	Status-Sharing	Shared traffic conditions
Class B	Intent-Sharing	Shared maneuver intent
Class C	Agreement-Seeking	Shared maneuver planning
Class D	Prescriptive	Action directing

Early research some 20 years ago considered multiple vehicles connected using infrared light or 5.8 GHz DSRC [38]. Other wireless technologies tested for use in CDA include Wi-Fi, Bluetooth, and satellite communication systems [39]. Due to the ubiquitous cellular infrastructure available in most areas, cellular communication and emerging 5G technology is being integrated with vehicles to create a connected intelligent vehicle framework [40].

To function effectively, a connected vehicle must be in a network with other connected vehicles and infrastructure. A study by Priemer and Friedrich [41] found that about 33% connected vehicle market share is required to have a visible effect on intersection traffic. Increasing CDA market share further improves control algorithm performance up to 90%, as additional adoption results in diminishing returns [42]. An IEEE news article [43] forecasted that 75% of all vehicles will be connected by 2040. To reach this goal, it is vital that CDA technologies are accepted by consumers. A major factor in consumer acceptance is product cost. Based on analysis of consumer trends, it was found that achieving a near-homogenous CDA population by 2050 would require annual connected vehicle price drops of 15 to 20 percent [44]. Additionally, governments will need to invest in connected infrastructure to meet this demand. The higher relative costs for disadvantaged communities could delay adoption of CDA [45].

While recent advances in connectivity, sensors, and ADAS technology are needed for CDA, many questions remain to be answered, such as safety, traffic negotiation, infrastructure, economics, and environmental impacts. In this thesis, the question on the fuel economy impacts of CDA will be addressed for zero emission electric drivetrain vehicles.

A review article by Zhang et al. [46] presents a variety of studies regarding the fuel economy and environmental impacts of CDA. Some studies indirectly address these concerns by considering time savings at intersections. For example, Ilgin Guler, Menendez, & Meier [47] found that CDA with a penetration rate of 60% could reduce delay at intersections by up to 60%. While not explicitly stated, it can be inferred that lower waiting times will result in less fuel use. Other research has shown that CDA can decrease fuel use and greenhouse gas emissions. A study by Wang et al. [48] found that CDA can decrease fuel consumption of a single vehicle by 2.63% for urban driving and 1.14% for highway driving when compared to the preceding connected autonomous vehicle. When CDA is deployed in a platoon, energy savings were found to be 16.1% for urban driving and 6.2% for highway driving [49]. By taking into account human error in vehicle tracking, Zhang et al. [50] found that energy consumption would decrease by 11.8% in simulations and 4.9% in real world tests. The authors note that their simulations do not account for situations with saturated vehicle traffic; additional optimizations must be made to ensure that simulated scenarios align with real world conditions. One study by Btutakov & Ioannou [51] found that altering traffic light algorithms to optimize a person's natural driving pace could save up to 60% of energy. The research of Brown, Gonder, & Repac [52] and Wadud, MacKenzie, & Leiby [53] noted that the adoption of CDA could increase the amount of fuel use and greenhouse gases released due to increased vehicle travel. While total VMTs may increase due to CDA, the fuel use per mile is expected to decrease.

2.2 Zero-Emission Vehicles

Previous studies on the impacts of AVs and CDA do not fully address the advances in alternative fuel powertrains, especially those that are zero-emission. The most popular alternative fuels being used today for ZEVs are electricity and hydrogen. An advantage ZEVs have over conventional vehicles is the lack of carbon and pollutant tailpipe emissions. The transition to ZEVs in response to California's 2035 zero-emission mandate is expected to reduce greenhouse gas and nitrogen oxides emissions by 35% and 80%, respectively [3]. Automakers are planning to reach this goal by offering a 100% zero-emission fleet in the near future: General Motors announced in 2021 that 100% of its new vehicles sold in 2035 will have zero tailpipe emissions, a step for the company's plan to be carbon neutral by 2040 [54].

2.2.1 Battery Electric Vehicles

The electric vehicle, invented by William Morrison in 1890, was the most popular automobile available before the introduction of affordable ICVs with Henry Ford's Model T [55]. Electric vehicles disappeared from the market due to the availability and affordability of crude oil and lack of electricity distribution outside of cities. Environmental legislation and awareness of the harmful effects of fossil fuels on our environment have renewed interest in BEVs. While several automakers, such as General Motors, Ford, Toyota, and Honda, prototyped BEVs in the late 1990's and early 2000's, none were able to bring them to the market due to high costs and safety concerns [56]. Major automakers began intensifying their research and development of BEVs after the success of Tesla Motors. Today, the high cost of gasoline and diesel has accelerated interest and demand for BEVs: Tesla recorded an 80% increase in sales in first three months of 2022 when compared to the previous year [57].

BEVs rely solely on a large traction battery to power the vehicle, leading to zero tailpipe emissions. An example of a BEV powertrain is shown in Figure 6. Electricity is stored in the battery by plugging into and recharging from the power grid. While BEVs have a high efficiency, they suffer from limited range and slow recharging times [58]. New advances in battery and recharging technology have addressed these shortcomings: Tesla's Model 3 has a range of over 300 miles and can charge 180 miles of range in 15 minutes at a third generation 250-kW peak Supercharger [59].

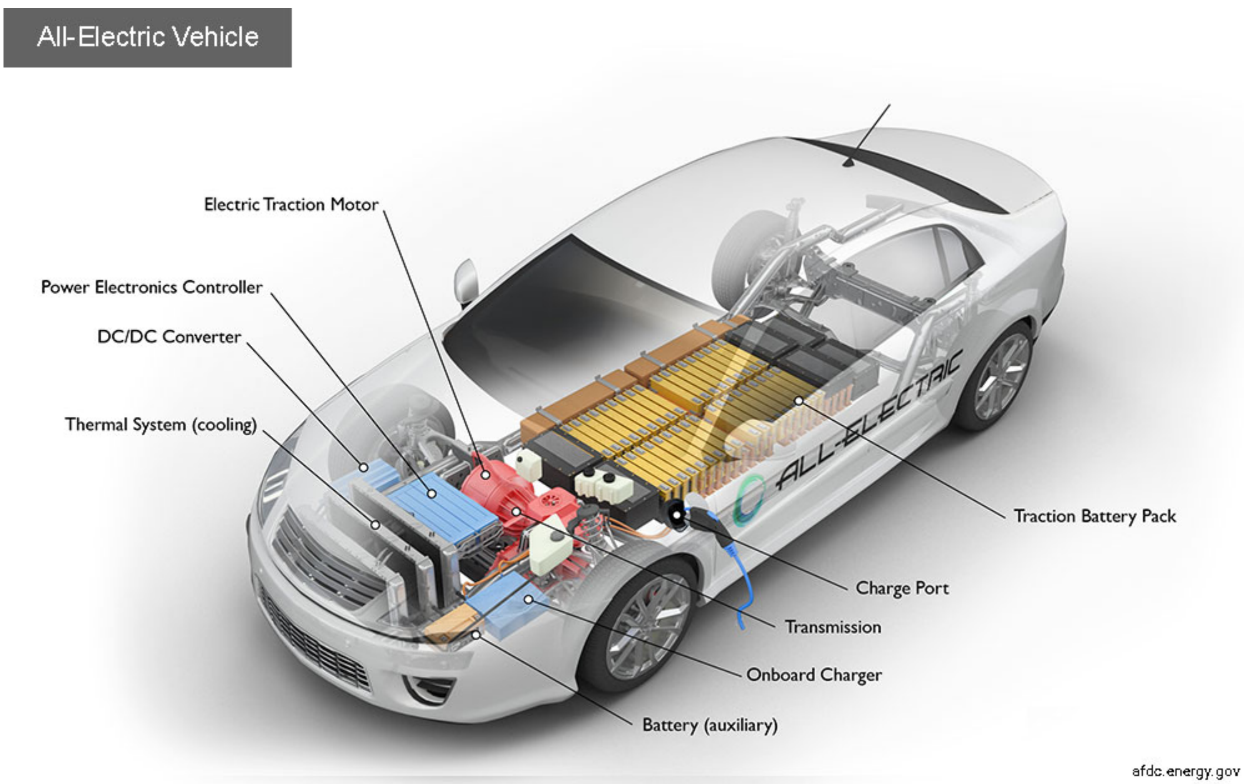

Figure 6. Battery Electric Vehicle Powertrain, from [60]

While BEVs have no tailpipe emissions, the true environmental impact and fuel use depends on the on the method the electricity it uses is produced. The use of coal or natural gas to generate electricity is still popular in many locations around the world; BEVs that utilize this energy transfer their emissions to electricity generators. For BEVs to be a truly low emission method of transportation, renewable electricity sources, such as wind, solar, and hydroelectricity, are required. Consumers heavily factor the cost of refueling when deciding on purchasing a vehicle. The energy cost per mile for a BEV is much less than an ICV: at the average electricity cost of ten cents per kWh, a BEV with an efficiency of three miles per kWh would cost 3.3 cents per mile, while at a price of $3.50 per gallon of gasoline, an ICV with an efficiency of 22 miles per gallon would cost 15.9 cents per mile [61]. Consumers could save additional money if CDA technology is used with BEVs: a study by Islam, Aziz, Wang & Young found that a 100% connected BEV fleet could reduce energy use by 20-40% when compared to a 0% BEV fleet [42].

2.2.2 Fuel Cell Electric Vehicles

Fuel cells are an electrochemical device that produces electricity using a fuel (usually hydrogen) that undergoes a pair of oxidation-reduction reactions [62]. A FCEV combines the electrochemical energy of a fuel cell and an electric motor for propulsion. FCEVs today utilize a proton exchange membrane (PEM) fuel cell due to its relatively low temperature and ability for dynamic output demands. An example of a FCEV powertrain is shown in Figure 7. Because of the chemical reaction of hydrogen and oxygen in the fuel cell, water is the sole emission of a FCEV.

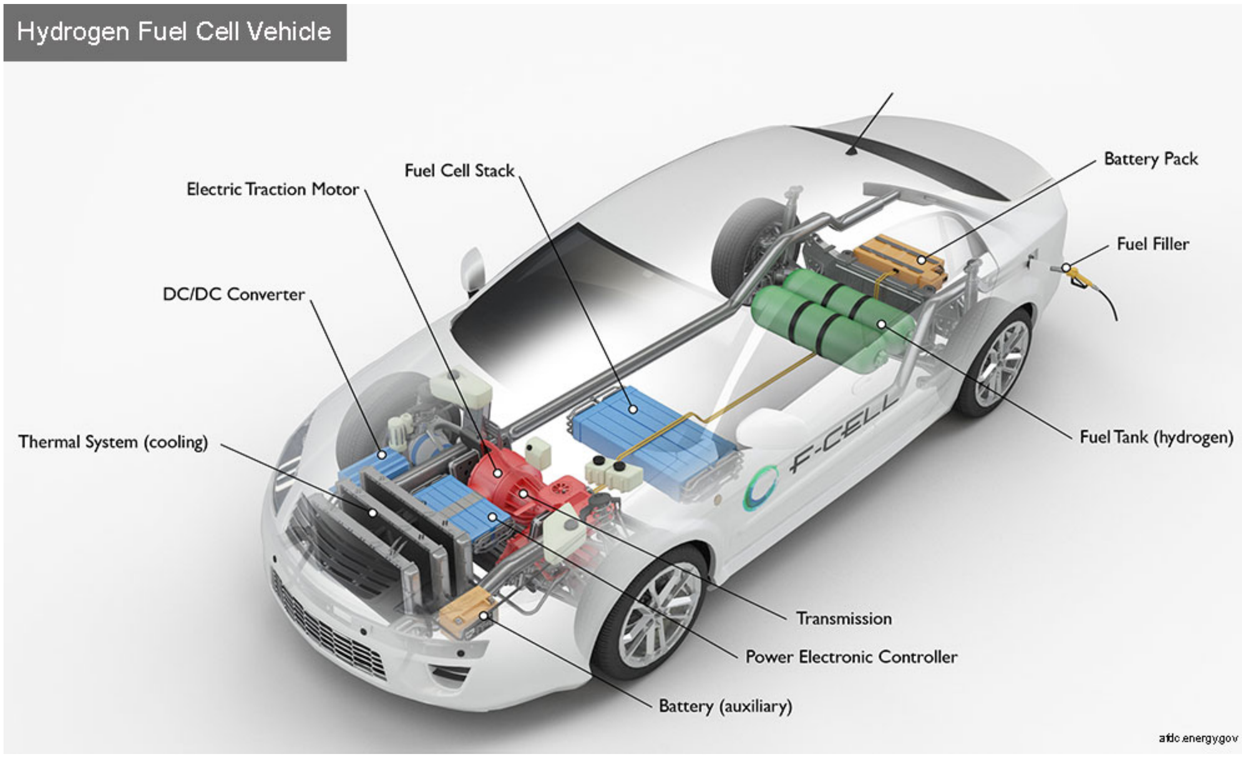

Figure 7. Hydrogen Fuel Cell Electric Vehicle Powertrain, from [63]

The first fuel cell used to power a vehicle was demonstrated by General Motors in 1966, but was discontinued due to high costs and lack of hydrogen infrastructure [64]. Much like BEVs, FCEVs have been pursued as a viable option for zero-emission mobility due to environmental legislation and climate change awareness. The 2015 Hyundai Tucson Fuel Cell and Toyota Mirai were among the first FCEVs commercially available to purchase [64]. FCEVs benefit from having long range and short refueling times that are comparable to conventional ICVs. Current hydrogen refueling stations for light duty vehicles are capable of delivering 5 kg of hydrogen at 70MPa in roughly 5 minutes [65].

Current barriers for FCEV adoption include the lack of refueling infrastructure and high price of hydrogen. Currently no hydrogen fueling stations exist in the United States outside of California or Hawaii. As of June 2021, there are 52 hydrogen refueling stations in California, with a total of 176 retail hydrogen stations to be opened by 2026 [66]. A network of hydrogen stations throughout the U.S is needed to promote the adoption of FCEVs. Hydrogen production has many pathways, some of which are shown in

Table 3. For FCEVs to be low or zero emission, the hydrogen produced must be blue or green. While no study today compares the benefits of connected FCEVs to other vehicle types, FCEVs will be important for the zero-emission future.

Table 3. Hydrogen Production Methods, from [67]

Hydrogen Type	**Production Method**
Brown hydrogen	Steam reformation of coal
Gray hydrogen	Steam reformation of natural gas
Blue hydrogen	Steam reformation of natural gas with carbon capture
Green hydrogen	Electrolysis of water

2.3 Drive Cycles

Drive cycles play an important role in determining the fuel efficiency of a vehicle because they replicate the driving behavior of a typical driver. The EPA evaluates the emissions of vehicles using a set of five drive cycles: city, highway, high speed, air conditioning, and cold temperature [68]. Additional test procedures are detailed for electric and plug-in hybrid vehicles using the SAE J1634 standard [69]. Fuel economy for gasoline vehicles is determined by measuring the carbon emissions while fuel economy for electric vehicles is determined by measuring electricity usage per distance traveled. Each test procedure used is derived from the urban and highway drive cycles. The Urban Dynamometer Driving Schedule (UDDS), also known as the LA4 road route, was developed in 1973 to characterize urban traffic in Los

Angeles, as shown in Figure 8. The Federal Test Procedure (FTP) builds on this by taking the original UDDS and adding an additional hot start phase consisting of the first 505 seconds of the UDDS for emission and fuel economy calculations. Similarly, the Highway Fuel Economy Driving Schedule (HWFET) drive cycle was developed in 1974 to characterize vehicle travel along highways near Ann Arbor, Michigan, as shown in Figure 9. These drive cycles, which were developed nearly half a century ago, may not accurately depict current traffic conditions. Furthermore, the currently used drive cycles will not accurately represent current and particularly future ZEVs equipped with CDA because of their smoother driving characteristics. This study aims to develop and demonstrate an analysis framework for a set of CDA enabled drive cycles that will properly reflect the future of mobility.

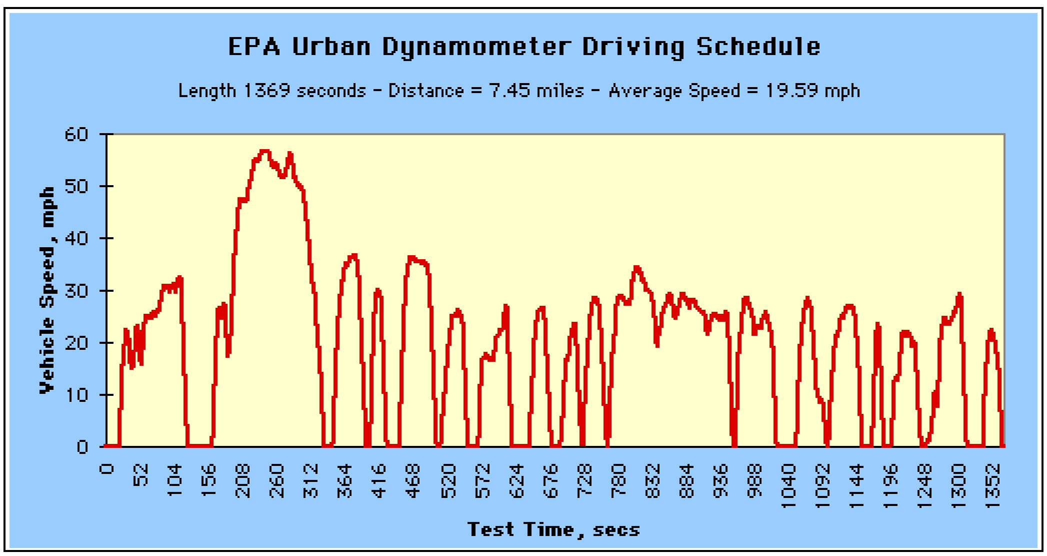

Figure 8. Urban Dynamometer Driving Schedule, from [70]

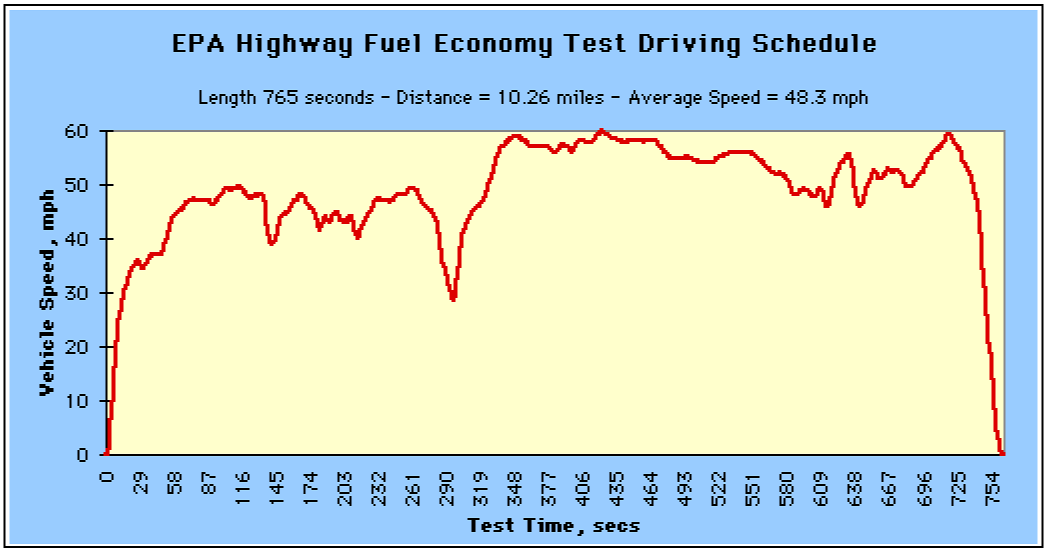

Figure 9. Highway Fuel Economy Test Driving Schedule, from [70]

2.4 Vehicle Simulation Tools

This thesis utilizes the Future Automotive Systems Technology Simulator (FASTSim), developed by the National Renewable Energy Laboratory (NREL). FASTSim is a tool that utilizes simplified powertrain systems to estimate impacts of technological improvements on vehicle efficiency. Its validated high-level powertrain analysis capabilities allow for quick and accurate simulations on vehicle energy usage.

Other vehicle simulation tools were investigated, including multiple models developed on the MathWorks' MATLAB/Simulink platform. Simulink offers powerful toolboxes, such as the powertrain blockset, vehicle dynamics blockset, and automatic driving toolbox, that can simulate detailed models of zero-emission powertrains and CDA scenarios. These toolboxes also offer premade vehicle powertrain and ADAS scenario models that showcase the software's simulation capabilities. Detailed BEV and FCEV models utilizing MATHWORK's Simulink software were investigated for this study but were rejected due to the varying complex systems in each model.

2.5 Scope of Current Work

With zero-emission powertrains and CDA emerging as the future of mobility, it is prudent to address impacts on fuel (electricity and hydrogen) in order to (1) inform both vehicle and CDA design to optimize fuel reduction associated with this paradigm shift, and (2) characterize the energy efficiency for the next-generation "Monroney sticker." To address this requirement, this study develops a methodology to establish the potential fuel savings of ZEVs equipped with CDA.

While previous studies address the environmental and fuel economy impacts of CDA, most focus on time savings at intersections. Given that the impact of CDA on individual traffic events at intersections does not fully encompass the full energy benefit of CDA, this study considers as well the impact of CDA on the vehicle drive cycle.

In addition, prior studies do not address the advances in alternative fuel powertrains, especially those that are zero-emission. Environmental impacts and rising prices of fossil fuels have recently made both BEVs and FCEVs grow in popularity. Both technologies will be vital in the transition to a zero-emission future. Therefore, this thesis addresses CDA equipped on both BEVs and FCEVs.

Overall, the current work develops and applies an analysis framework to evaluate the potential fuel savings of ZEVs equipped with CDA.

3. Approach

Task 1: Analyze and select CDA scenarios and a powertrain simulation model

A powertrain model that accurately simulates a BEV and FCEV is necessary to establish a baseline for drive cycle testing. New powertrain models do not need to be developed as many validated models already exist. The purpose of this task is to explore and evaluate established BEV and FCEV models for accuracy, detail, and ease of use. Drive cycles that characterize vehicles equipped with CDA will be selected.

Task 2: Develop a Methodology that Incorporates the Powertrain Model to address CDA Fuel Use Impacts

A methodology will be developed that determines potential energy and fuel cost savings of vehicles equipped with CDA. This methodology will utilize previously selected CDA drive cycles and powertrain models to investigate potential energy impacts caused by V2V and V2I enabled connectivity.

Task 3: Test CDA Drive Cycles using the Selected Powertrain Model

The base EPA drive cycles and the resulting CDA drive cycles will be tested using the selected powertrain models. A sensitivity analysis on powertrain components utilizing the EPA and CDA drive cycles will also be performed to evaluate how different component efficiencies could affect fuel economy.

Task 4: Apply the Methodology to Analyze and compare powertrain models on fuel use with and without CDA

Energy usage data from the base and CDA drive cycles will be gathered to characterize a set of fuel economy ratings. Potential energy savings between CDA fuel economy ratings and current EPA fuel economy ratings will be analyzed. Additionally, an analysis on the cost to operate vehicles with and without CDA will be conducted.

4. METHODOLOGY

4.1 Zero-Emission Powertrain Modeling

To study the energy impacts on vehicles due to connectivity, accurate powertrain models must be used. In the present work, vehicle powertrains are modeled using FASTSim software [71]. While more detailed powertrain models could provide more insight into the dynamics of each powertrain component, the complexity of each component introduces uncertainty that could compound and invalidate results [72]. Using simple models allows for sources of uncertainty to be limited, making results more trustworthy. Each powertrain component in FASTSim is validated against efficiency and thermal maps of real-world components, such as motors, batteries, and fuel cells, to offer models with low amounts of uncertainty [73]. In this study a variety of battery-electric and fuel cell-electric powertrains were modeled to determine the consistency of energy impacts due to connectivity. A list of the models provided in FASTSim and used in the present work is shown in Table 4.

Table 4. Vehicles Modeled in FASTSim

Vehicle	**Powertrain Type**
Tesla Model S	Battery-Electric
Nissan Leaf	Battery-Electric
Toyota Mirai	Fuel Cell-Electric
Hyundai Tucson	Fuel Cell-Electric

4.1.1 Battery Electric Vehicle Models

This section details the two battery-electric vehicles that were modeled in FASTSim. Two BEVs were simulated for this study to determine the consistency of energy impacts due to connectivity.

4.1.1.1 Tesla Model S

The first vehicle modeled was a Tesla Model S, a performance liftback BEV. This model replicates the 2016 rear-wheel drive trim of the vehicle. Specifications for the Tesla Model S are shown in Table 5.

Table 5. 2016 Tesla Model S RWD Specifications

Weight	4705 lbs
Motor	285 kW
Battery	75 kWh
Frontal Area	2.832 m^2
Drag Coefficient	0.3

4.1.1.2 Nissan Leaf

The second vehicle modeled was a Nissan Leaf, a compact hatchback BEV. This model replicates the 2016 30 kWh battery trim of the vehicle. Specifications for the Nissan Leaf are shown in Table 6.

Table 6. 2016 Nissan Leaf 30kWh Specifications

Weight	3307 lbs
Motor	80 kW
Battery	30 kWh
Frontal Area	2.755 m^2
Drag Coefficient	0.315

4.1.2 Fuel Cell Electric Vehicle Models

This section details the two fuel cell-electric vehicles were modeled in FASTSim. A pair of FCEVs were simulated in this study to determine the consistency of energy impacts due to connectivity.

4.1.2.1 Toyota Mirai

The third vehicle modeled was a Toyota Mirai, a mid-sized sedan FCEV. This model replicates the 2016 model year of the vehicle. Specifications for the Toyota Mirai are shown in Table 7.

Table 7. 2016 Toyota Mirai Specifications

Weight	3954 lbs
Motor	113 kW
Battery	1.6 kWh
Fuel Cell	114 kW
Frontal Area	2.786 m^2
Drag Coefficient	0.3

4.1.2.2 Hyundai Tucson

The final vehicle modeled was a Hyundai Tucson, a crossover sport utility vehicle FCEV. This model replicates the 2016 fuel cell variant of the vehicle. Specifications for the Hyundai Tucson are shown in Table 8.

Table 8. 2016 Hyundai Tucson Fuel Cell Specifications

Weight	4500 lbs
Motor	134 kW
Battery	1 kWh
Fuel Cell	134 kW
Frontal Area	3.016 m^2
Drag Coefficient	0.355

4.2 Drive Cycle Modeling

The US EPA determines vehicle fuel economy and emissions in accordance with part 600 of Title 40 of the United States Code of Federal Regulations (C.F.R.). Since 2008, the US EPA has required five different laboratory tests to determine vehicle fuel efficiency: city, highway, high speed, air conditioning, and cold temperature [68]. A method for determining fuel economy listed in 40 C.F.R 600.210-12 can derive a 5-cycle fuel economy using only the city and highway laboratory tests [74]. A spreadsheet that was produced in Microsoft Excel by the US EPA was used to determine the 5-cycle fuel economies for this study [75]. Equations for the derived 5-cycle city and highway fuel economies are shown in Equations 1 and 2. The city and highway intercept and slope values are determined by the EPA based on historical vehicle-specific 5-cycle city and highway fuel economy data [74]. *FTP FE* refers to fuel economy from the city test, while *HWFET FE* refers to fuel economy from the from the highway test.

$$Derived\ City\ Fuel\ Economy = \frac{1}{\left(City\ Intercept + \frac{City\ Slope}{FTP\ FE}\right)} \tag{1}$$

$$Derived\ Highway\ Fuel\ Economy = \frac{1}{\left(Highway\ Intercept + \frac{Highway\ Slope}{HWFET\ FE}\right)} \tag{2}$$

4.2.1 City Drive Cycle

To determine fuel economy for the city test, the FTP drive cycle, developed by the US EPA, is used [70]. The FTP, created by appending the first 505 seconds of the UDDS to itself, is an 11-mile drive cycle that includes many accelerations and decelerations to mimic driving in an urban environment. The speed trace of the FTP is shown in Figure 10.

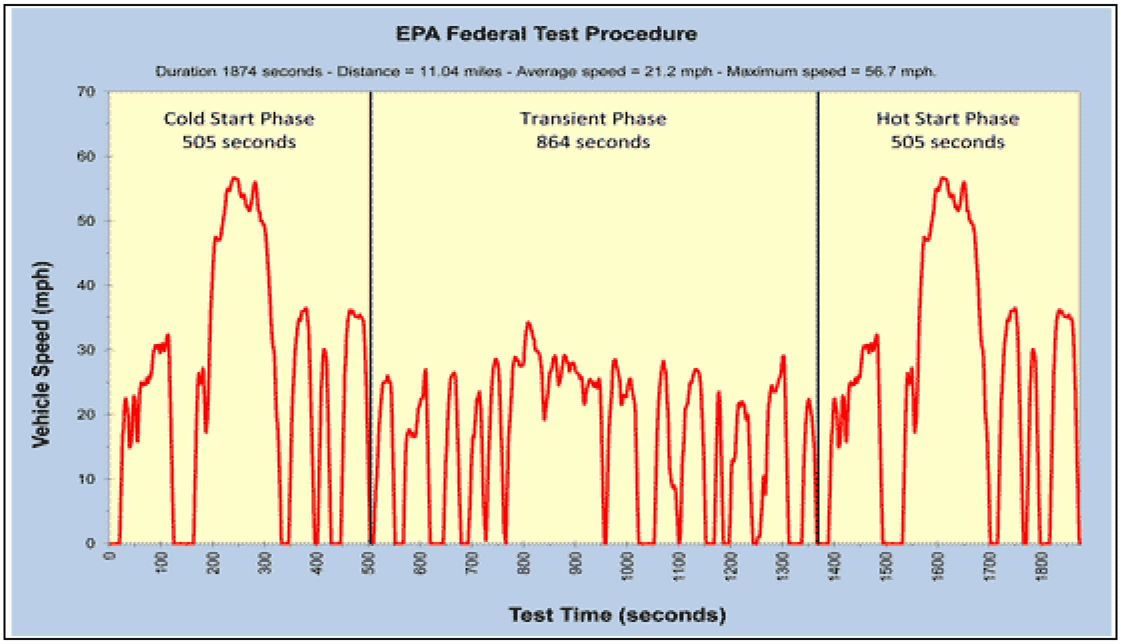

Figure 10. Federal Test Procedure Speed Trace, from [70]

The many accelerations and decelerations in the FTP can be attributed to stoplights, hazards, or traffic typical in urban environments. With the addition of connectivity, vehicles could receive advanced warnings of hazards from other vehicles or infrastructure, which could reduce the instances of accelerations and decelerations.

A series of drive cycles were created by Dr. Van Wifvat in a study from the University of California, Irvine to simulate the effects of connectivity. Wifvat augmented the UDDS drive cycle by assuming that each stop was the result of a traffic light, as shown in Figure 11 [76].

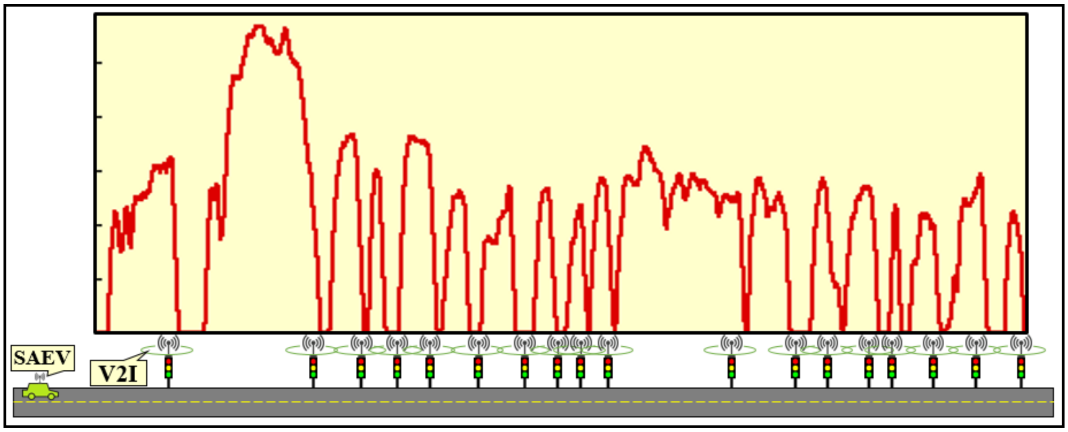

Figure 11. FTP V2I Schematic, from [76]

If each traffic light were transformed into a V2I-enabled traffic light, vehicles would be warned to reduce speeds preemptively, which would prevent unnecessary stop-and-go behavior. Smoothing out the UDDS drive cycle presents an opportunity for vehicles to obtain greater fuel efficiency.

The augmented UDDS drive cycles were appended with the first 505 seconds of itself to create the augmented FTP drive cycles. Three different drive cycles were created to represent three different ranges of DSRC connectivity: 250m, 350m, and 450m, as shown in Figure 12. Figure 13 shows a selected section that highlights the smoothing out V2I communication can achieve. The three V2I drive cycles were input into FASTSim to determine possible energy savings in ZEVs in urban driving.

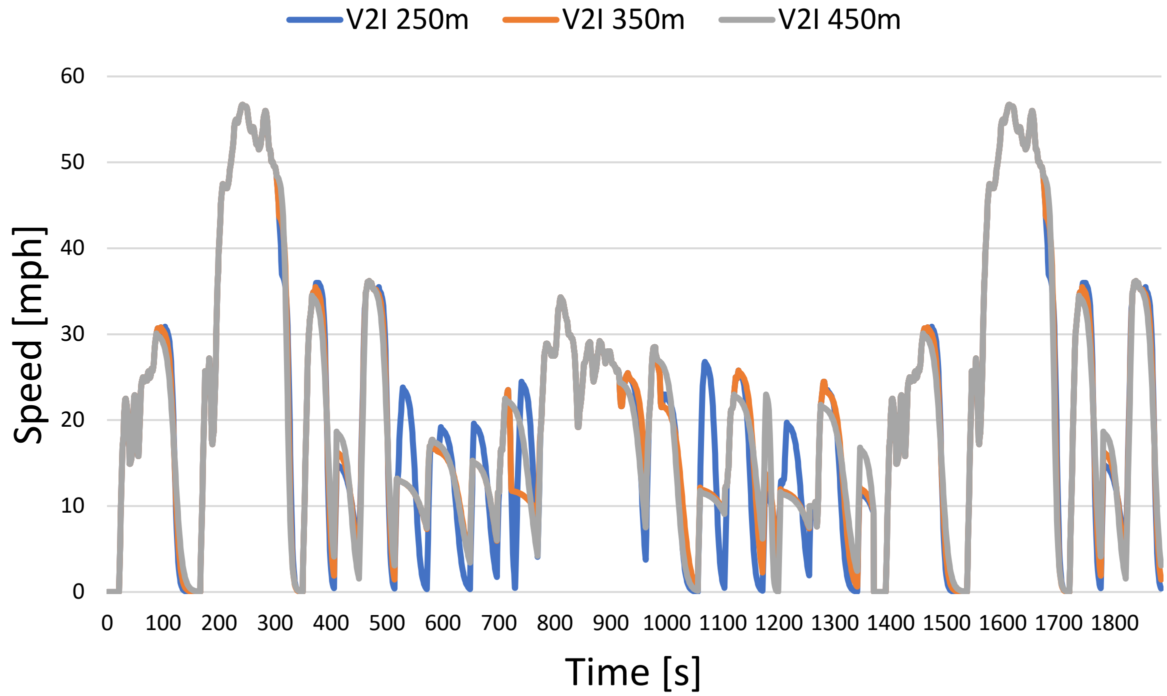

Figure 12. V2I Drive Cycle, data from [76]

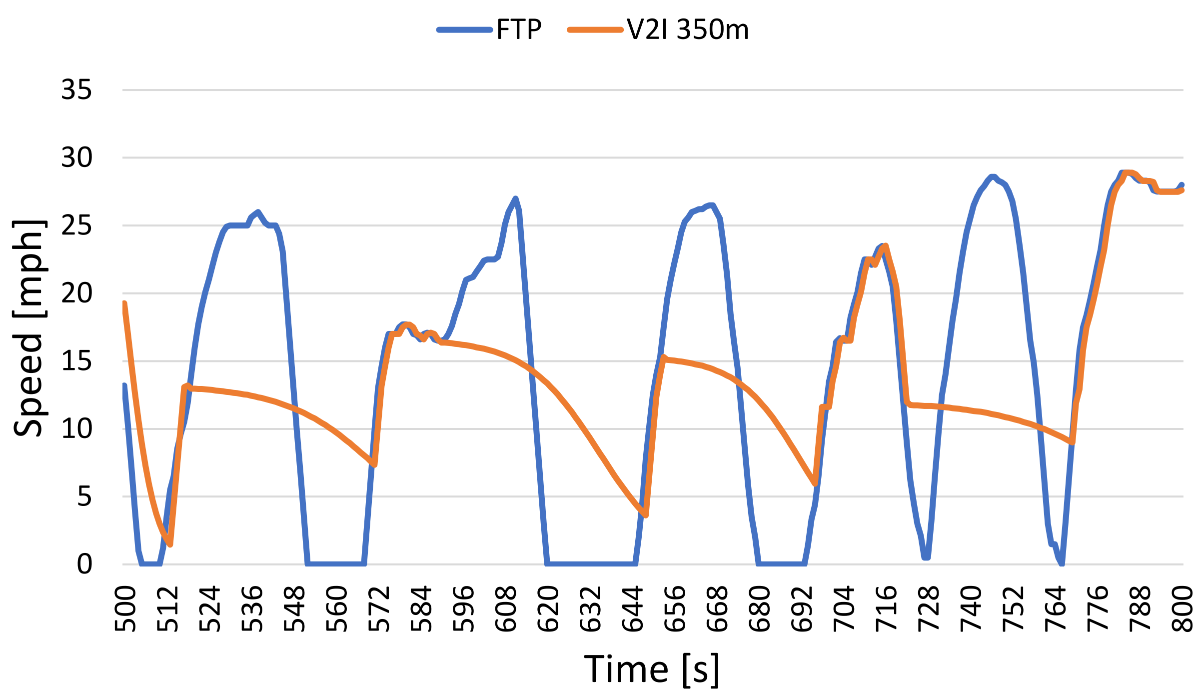

Figure 13. Comparison of FTP With and Without V2I Connectivity, data from [76]

4.2.2 Highway Drive Cycle

To determine fuel economy for the highway test, the HWFET drive cycle, developed by the US EPA, is used [70]. The HWFET is a 10-mile drive cycle that features accelerations to a high speed to mimic driving on a freeway. The speed trace of the HWFET is shown previously in Figure 9.

Unlike the FTP, the HWFET has a relatively smooth driving profile that would not benefit greatly from advanced warnings from V2I connectivity. Instead, fuel savings could be produced by platooning enabled by V2V communication. Equation 3 shows the formula for the force of drag, where F_D is the force of drag, ρ is fluid density, C_D is the drag coefficient, and A is the frontal area. Because aerodynamic drag varies directly with the square of velocity, drag force becomes a larger factor in vehicle dynamics at highway speeds. Platooning vehicles close together could reduce the effect of drag on a fleet of vehicles.

$$F_D = \frac{1}{2}\rho v^2 C_D A \tag{3}$$

Previous studies have shown that platooning vehicles can reduce vehicle drag. Studies by Zabat et al. (1994) found that scale model platoons of 2 to 4 minivans at half of a car length apart could reduce drag by 25% to 38% [77]. Another study by Schito et al. (2012) used Computational Fluid Dynamics (CFD) to find that homogenous and mixed vehicle fleets had the potential to reduce drag coefficients by 20% to 60% [78]. Drag reductions from platooning are not limited to following vehicles. A CFD study from Ebrahim & Dominy (2020) found that leading vehicles had a reduction in drag caused by the pressure increase on the wake by trailing vehicles [79]. These studies show that drag reductions are dependent on vehicle geometry, location, speed, and following distance.

In this study, drag reductions by platooning will be evaluated. Because of the variations in drag reductions, multiple cases will be studied. Drag coefficients will be reduced by 10%, 20%, and 40% to determine potential energy savings in ZEVs for highway driving. The drag coefficient reduction of 40% was chosen as an upper limit to represent the average drag reduction of an entire fleet.

4.3 Drive Cycle Testing

This section details the additional parameters used for each FASTSim model to evaluate potential efficiency gains from vehicle-to-everything (V2X) communication.

4.3.1 Vehicle Sensor Installation

Future vehicles with equipped with CDA will require a suite of ADAS sensors. While the addition of CDA may improve fuel economy, the installation of ADAS sensors and its accompanying equipment will have an operational cost caused by the increase in weight and power consumption. In this study, the weight and auxiliary load of a CDA system is included into the FASTSim vehicle models. CDA equipment was estimated to have a mass of 10kg and auxiliary load of 75W, based on estimates from Tesla on sensor and wiring mass and power usage in their FSD product [80]. The addition of these sensors is not expected to increase the frontal area of the vehicle affected by aerodynamic drag.

4.3.2 Vehicle Simulations

This research also studies the effect of component performance on fuel consumption and connectivity. One component was modified for each powertrain type to perform a sensitivity analysis.

4.3.2.1 Battery Roundtrip Efficiency

One critical parameter that can be varied for a BEV model in FASTSim is the roundtrip efficiency of the traction battery. The roundtrip efficiency refers to the amount of electricity that is discharged by energy storage for a given amount of charged electricity. In the case of utility-scale batteries and pumped hydropower storage for power grids, the roundtrip efficiency of the battery is approximately 80% [81]. A study by Schimpe et al. that analyzed lithium-ion batteries found that the conversion roundtrip efficiency ranges between 70% to 80% [82] . In FASTSim, the default roundtrip efficiency for traction batteries is given as 97%. For this study, three cases of roundtrip efficiency for BEV traction batteries were tested: 75%, 97%, and 100%. The 75% roundtrip efficiency represents the median efficiency of a typical lithium-ion battery, while the 97% roundtrip efficiency represents the default validated parameter within FASTSim. A hypothetical 100% roundtrip efficiency was also tested to determine how component efficiency improvements would change energy impacts due to connectivity.

4.3.2.2 Fuel Cell Efficiency

One critical parameter that can be varied for a FCEV model in FASTSim is the efficiency of the fuel cell. Fuel cell efficiency refers to the amount of energy of the electricity produced for a given amount of hydrogen fuel used. In most cases, the peak efficiency of a PEM fuel cell is 50% to 60% [83]. For a hydrogen-air fuel cell, the lowest value of maximum efficiency was found to be about 75% [84]. In FASTSim, the default maximum efficiency of the PEM fuel cell is 60%. For this study, three cases of fuel cell peak efficiency were tested: 50%, 60%, and 70%.

Figure 14 shows each case of the efficiency of the fuel cell for a given power output. Both 50% and 60% fuel cell efficiency represent possible efficiencies for current PEM fuel cells. The 70% fuel cell efficiency case represents possible efficiency gains from future technological improvements.

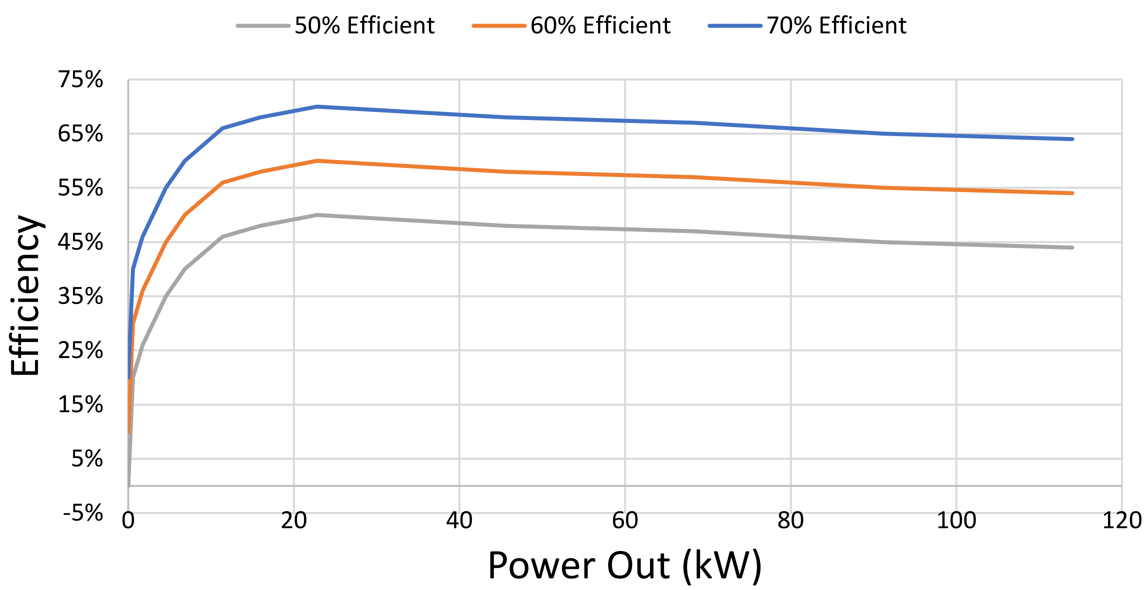

Figure 14. Fuel Cell Efficiency Map, from [71]

4.4 Cost Calculations

The last analysis of this work is the estimated annual fuel cost to operate each vehicle, a component of the Monroney sticker posted on all new cars sold in the US. Calculating these fuel prices for connected vehicles will help to illustrate additional savings compared to current conventional (i.e., non-connected) vehicles. This work will not account for the additional costs associated with electricity usage of connected infrastructure.

Equation 4 shows how to calculate the annual fuel expense for each vehicle, where MPGe is the combined miles per gallon equivalent for each vehicle and CGE is the cost of fuel per gallon equivalent for each vehicle type. For BEVs, the CGE is calculated by multiplying the price of electricity per kWh by 33.7, or the equivalent amount of electrical energy contained in one gallon of gasoline [85]. The CGE for FCEVs is the price of hydrogen per kilogram, as one kilogram of hydrogen has the same energy content as a gallon of gasoline [86]. The EPA estimates that today's new vehicles get 27 miles per gallon and are driven 15,000 miles per year [87].

$$AnnualFuelCost = \frac{15000}{MPGe} * CGE \tag{4}$$

For this study, two years were considered for analysis: 2021 and 2035. 2035 was chosen to better reflect fuel prices for ZEVs at the year where all new vehicles sold in California will be zero-emission. Gasoline and electricity prices were obtained from the US Energy Information Administration (EIA) [88]. Retail prices for dispensed hydrogen were obtained from NREL for 2021 [89] and from a project from the University of California, Irvine for 2035[90]. The projected price of hydrogen was given as a range to reflect uncertainties in the price of hydrogen production. Likewise, the price of electricity in 2035 was also expressed as a range to match its uncertainty. Fuel prices used for this study are shown in Table 9.

Table 9. Fuel Prices, 2021 and 2035, from [88]–[90]

	Gasoline [$/gallon]	Electricity [$/kWh]	Hydrogen [$/kg]
2021	3.56	0.17	16.07
2035	4.01	0.15 (low) 0.21 (high)	5.06 (low) 7.27 (high)

5. RESULTS and DISCUSSION

5.1 Standard City and Highway Fuel Economies

The baseline FTP and HWFET drive cycles were simulated for each of the FASTSim vehicle models. Resulting city and highway outputs were adjusted using the US EPA label calculator spreadsheet and are shown in Table 10 below.

Table 10. FASTSim Vehicle Base Fuel Economy

Vehicle	City MPGe	Highway MPGe	Combined MPGe
Tesla Model S	109	98	104
Nissan Leaf	140	116	129
Toyota Mirai	65	62	64
Hyundai Tucson FC	56	53	55

EPA reported fuel economies of the real-life versions of each FASTSim vehicle model are shown in Table 11 [91]–[93]. The model combined fuel economy differed from actual values by 6% for the Tesla Model S, 15% for the Nissan Leaf, 3% for the Toyota Mirai, and 10% for the Hyundai Tucson. For this study, only the fuel economies of the simulated models will be compared.

Table 11. Real-Life Vehicle Fuel Economy, from [91]–[93]

	City MPGe	Highway MPGe	Combined MPGe
Tesla Model S	97	100	98
Nissan Leaf	124	101	112
Toyota Mirai	66	66	66
Hyundai Tucson FC	49	51	50

5.1.1 V2I City Fuel Economy

Each FASTSim vehicle model was tested using the three V2I city drive cycles. The adjusted fuel economy results are shown in Table 12.

Table 12. City Fuel Economy with V2I Connectivity

	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
Tesla Model S	116	120	121
Nissan Leaf	146	151	152
Toyota Mirai	69	71	72
Hyundai Tucson FC	61	62	63

The percent improvement over the base city fuel economy due to V2I connectivity is shown in Figure 15.

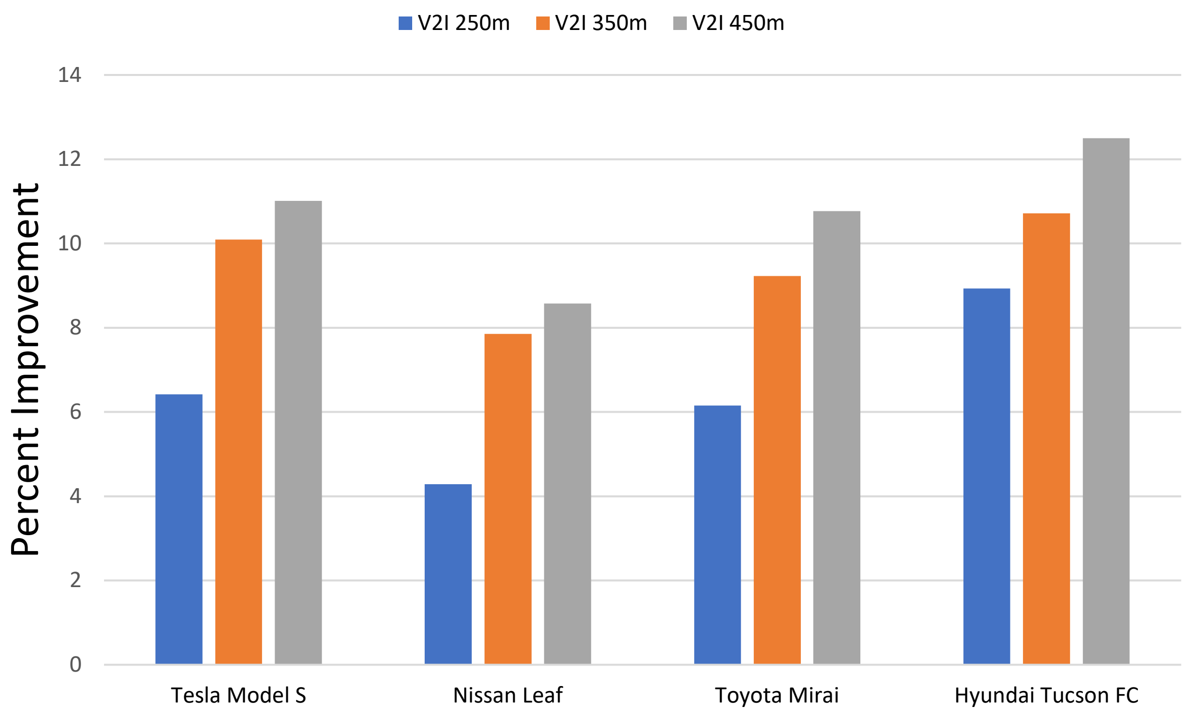

Figure 15. City Energy Improvements from V2I Connectivity

Overall, connectivity from 250 meters to 450 meters of range can improve city fuel economy from 6% to 12%. The Nissan Leaf had the lowest percent fuel economy improvements while the Hyundai Tucson had the highest overall percent fuel economy improvements. Base fuel economy for the Nissan Leaf was the highest at 140 MPGe, while the Hyundai Tucson had the lowest base fuel economy of 56 MPGe. The more efficient Nissan Leaf had a lower improvement due to connectivity than the less efficient Hyundai Tucson. This difference in fuel economy improvement could be attributed to less efficient vehicles having more available inefficiencies to extract energy savings from.

When comparing the 250 meter and 350 meter cases, the percent difference in improvement ranges from 20% for the Hyundai Tucson and 83% for the Nissan Leaf. Between the 350 meter and 450 meter cases, the percent difference in improvement ranges from 9% for the BEVs and 17% for the FCEVs. While the BEVs had the greater improvement when increasing the range from 250 meters to 350 meters, the FCEVs had the greater improvement when increasing the range from 350 meters to 450 meters. Each vehicle saw diminishing returns when increasing the connectivity range from 350 meters to 450 meters.

5.1.2 V2V Highway Fuel Economy

The results of the FASTSim vehicle models in the highway drive cycle at reduced drag coefficient are shown in Table 13.

Table 13. Highway Fuel Economy with V2V Connectivity

	10% C_d reduction	20% C_d reduction	40% C_d reduction
Tesla Model S	104	109	124
Nissan Leaf	123	131	153
Toyota Mirai	66	69	78
Hyundai Tucson FC	56	59	67

The percent improvement over the base highway fuel economy due to V2V platooning connectivity is shown in Figure 16.

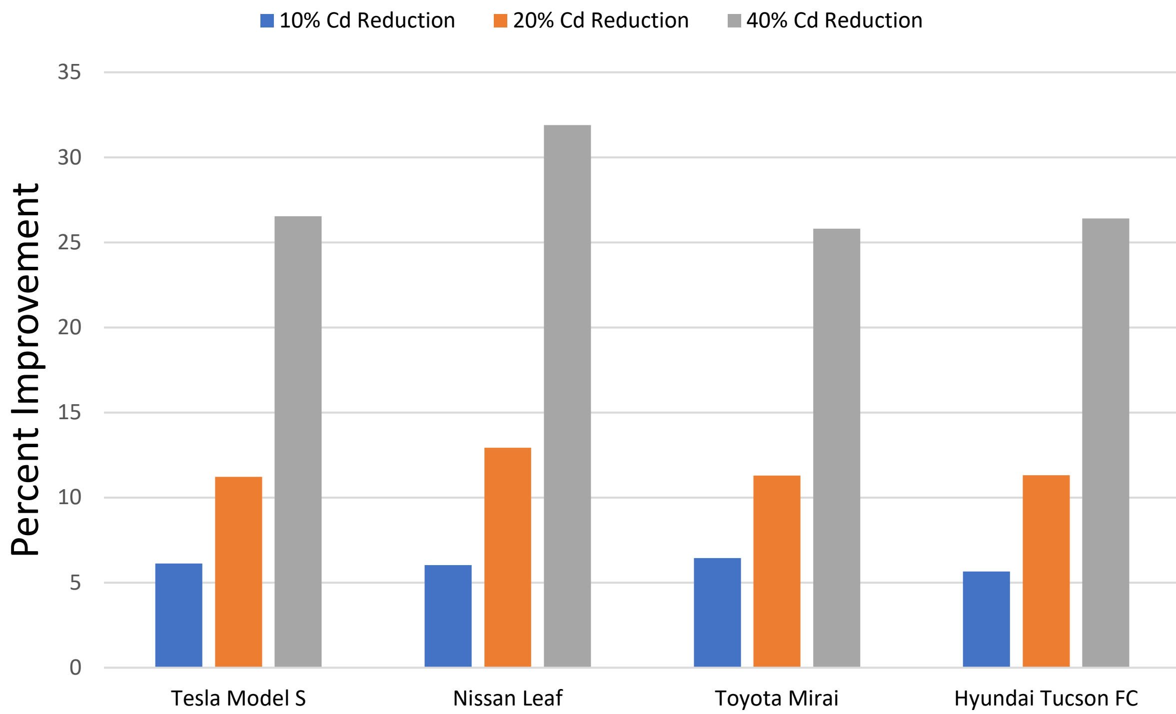

Figure 16. Highway Energy Improvements from Connectivity

Overall, the reduction in drag coefficients due to platooning could improve highway fuel economy by 6% to 32%. Each vehicle model had similar fuel efficiency gains from platooning. The data show that a nearly linear relation between drag coefficient reduction and fuel economy improvement exists. At 10% drag coefficient reduction, each vehicle had about 6% improvement in fuel economy. Doubling the drag coefficient reduction to 20% nearly doubles each vehicle's fuel economy improvement to about 11%. Further doubling the drag coefficient reduction to 40% also nearly doubles each vehicle's fuel economy improvement to about 26%. The Nissan Leaf had increased fuel economy improvements of 13% and 32% for the 20% and 40% drag coefficient reduction cases, respectively.

The similar improvements between each vehicle model could be explained by the drag force in vehicle dynamics, shown previously in Equation 3.. Because there is a linear relation between drag coefficient and drag force, reductions in drag coefficients will trace linearly to reductions in energy usage.

5.2 Vehicle Component Variations

Additional simulations were conducted that vary a specific powertrain component as a sensitivity analysis. For BEVs, the traction battery roundtrip efficiency was varied, while the fuel cell efficiency was varied for the FCEVs. Each component was tested using both the base and V2X connected drive cycles.

5.2.1 Battery Roundtrip Efficiency Variations

In addition to the standard 97% efficient traction battery, the Tesla Model S and Nissan Leaf were both simulated with a theoretical 100% and realistic 75% roundtrip efficient traction battery. Table 14 shows the adjusted city fuel economy for the base and V2I connected drive cycles, while Table 15 shows the adjusted highway fuel economy for the base and V2V platoon drive cycles. As expected, raising the battery efficiency increased fuel economy while lowering battery efficiency decreased fuel economy.

Table 14. Adjusted City Fuel Economy of Varied BEVs

	FTP	V2I 250m	V2I 350m	V2I 450m
Tesla Model S, 100% battery efficiency	112	118	123	123
Tesla Model S, 75% battery efficiency	86	94	98	99
Nissan Leaf, 100% battery efficiency	144	151	155	156
Nissan Leaf, 75% battery efficiency	112	120	124	126

Table 15. Adjusted Highway Fuel Economy of Varied BEVs

	HWFET	Cd 10%	Cd 20%	Cd 40%
Tesla Model S, 100% battery efficiency	100	105	112	127
Tesla Model S, 75% battery efficiency	84	89	94	105
Nissan Leaf, 100% battery efficiency	117	125	134	156
Nissan Leaf, 75% battery efficiency	99	106	113	130

Figure 17 and Figure ***18*** show the percent improvement over the FTP city fuel economy due to V2I connectivity for each variation and vehicle model. When comparing the city V2I drive cycles, the 75% efficient battery had a greater improvement from connectivity than the 100% efficient battery. This finding could be attributed to less efficient components having more available inefficiencies to extract energy savings from. Much like the base V2I city simulations, there were diminishing returns from increasing the V2I range past 350m.

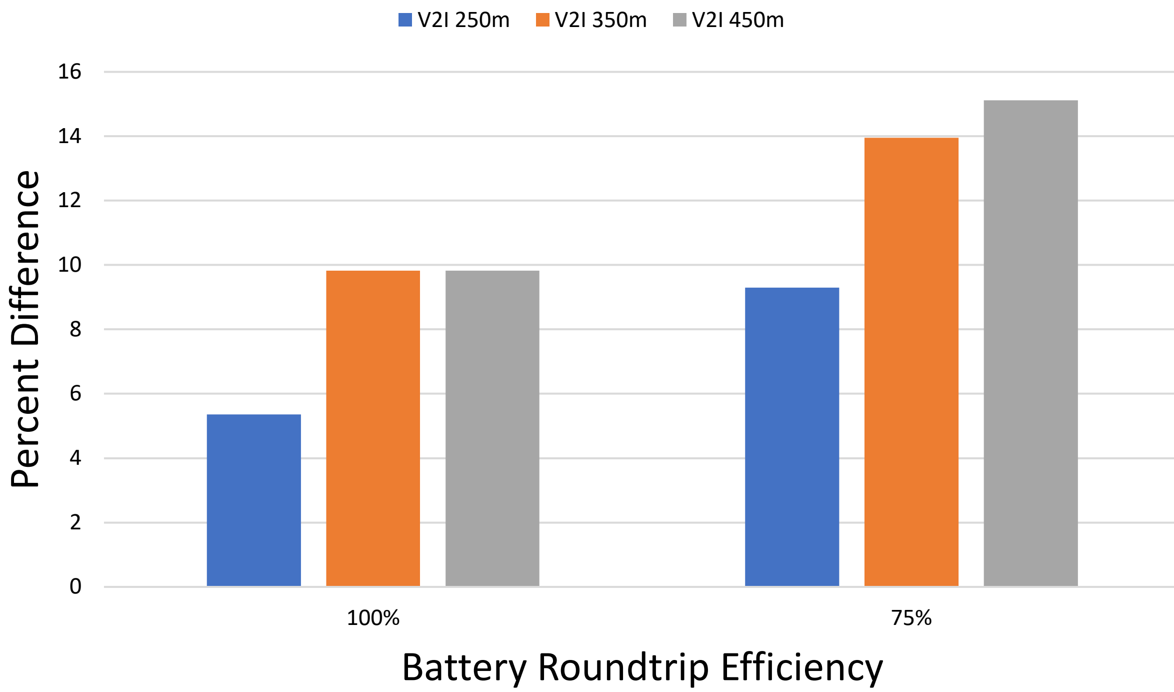

Figure 17. Tesla Model S City Energy Improvements with Variations and Connectivity

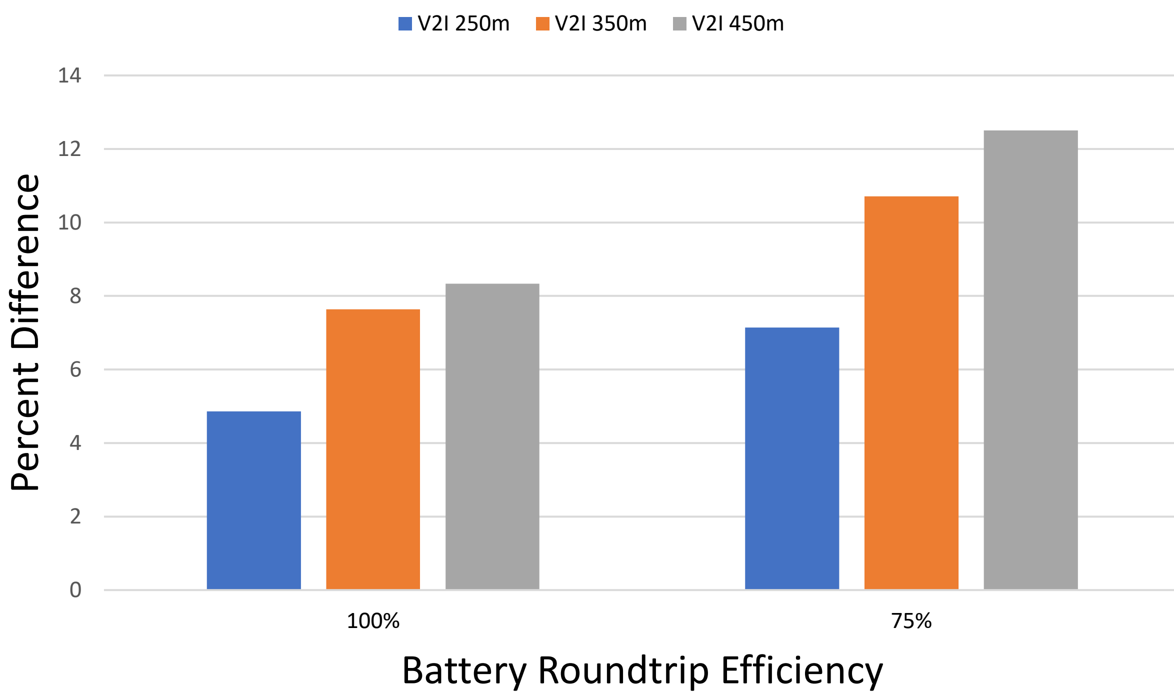

Figure 18. Nissan Leaf City Energy Improvements with Variations and Connectivity

Figure 19 and Figure ***20*** show the percent improvement over the HWFET highway fuel economy due to V2X connectivity for each variation and vehicle model. For the Tesla Model S, improvements ranged from 5% to 27%, while improvements for the Nissan Leaf ranged from 7% to 33%. Much like the base V2V highway simulations, improvements due to connectivity were linearly related; doubling the drag coefficient reduction nearly doubled the percent fuel economy improvement for each case. While both BEVs had similar improvements for each battery efficiency case, larger gains were noticed in the 100% efficient battery and 40% drag coefficient reduction case.

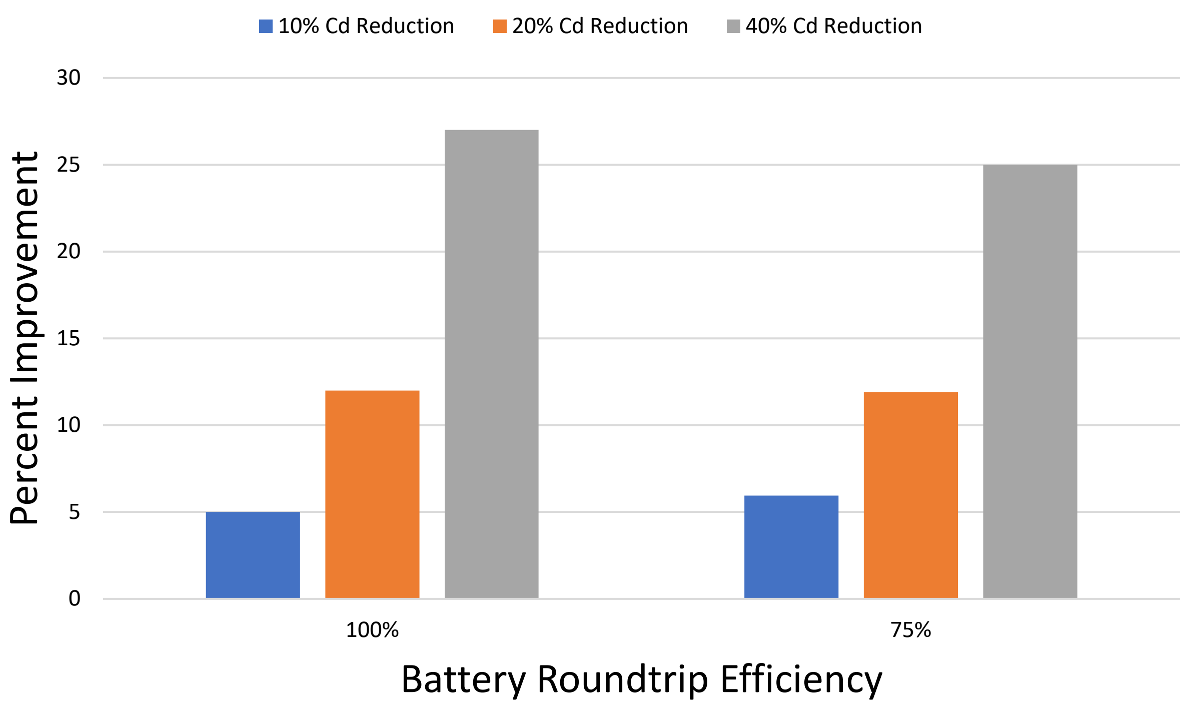

Figure 19. Tesla Model S Highway Energy Improvements with Variations and Connectivity

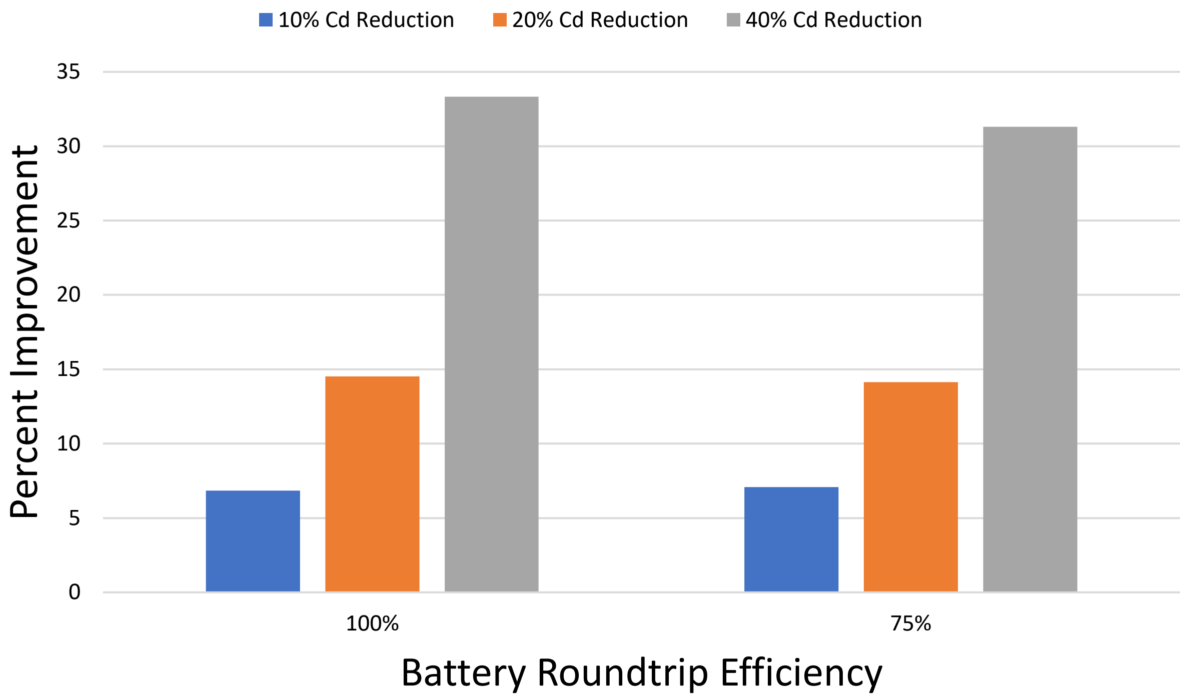

Figure 20. Nissan Leaf Highway Energy Improvements with Variations and Connectivity

5.2.2 Fuel Cell Efficiency Variations

In addition to the standard 60% peak efficiency fuel cell, the Toyota Mirai and Hyundai Tucson FC were both simulated with a 70% and 50% peak efficiency fuel cell. Table 16 shows the adjusted city fuel economy the base and V2I connected drive cycles, while Table 17 shows the adjusted highway fuel economy for the base and V2V platoon drive cycles. Again, higher efficiency components led to increased fuel economy while lower efficiency components led to decreased fuel economy.

Table 16. Adjusted City Fuel Economy of Varied FCEVs

	FTP	V2I 250m	V2I 350m	V2I 450m
Toyota Mirai, 70% peak efficiency fuel cell	78	83	85	87
Toyota Mirai, 50% peak efficiency fuel cell	51	55	56	57
Hyundai Tucson, 70% peak efficiency fuel cell	68	74	75	76
Hyundai Tucson, 50% peak efficiency fuel cell	43	48	49	49

Table 17. Adjusted Highway Fuel Economy of Varied FCEVs

	HWFET	C_d 10%	C_d 20%	C_d 40%
Toyota Mirai, 70% peak efficiency fuel cell	74	77	82	92
Toyota Mirai, 50% peak efficiency fuel cell	51	53	56	63
Hyundai Tucson, 70% peak efficiency fuel cell	62	66	70	79
Hyundai Tucson, 50% peak efficiency fuel cell	43	45	48	54

Figure 21 and Figure 22 show the percent improvement over the non-connected FTP city fuel economy due to V2I connectivity for each variation and vehicle model. In both vehicle models, the 50% efficient fuel cell had a greater improvement from V2I connectivity than the 70% efficient fuel cell. This finding is consistent with the findings from the BEV battery efficiency variations: less efficient components have more available inefficiencies to extract energy savings from.

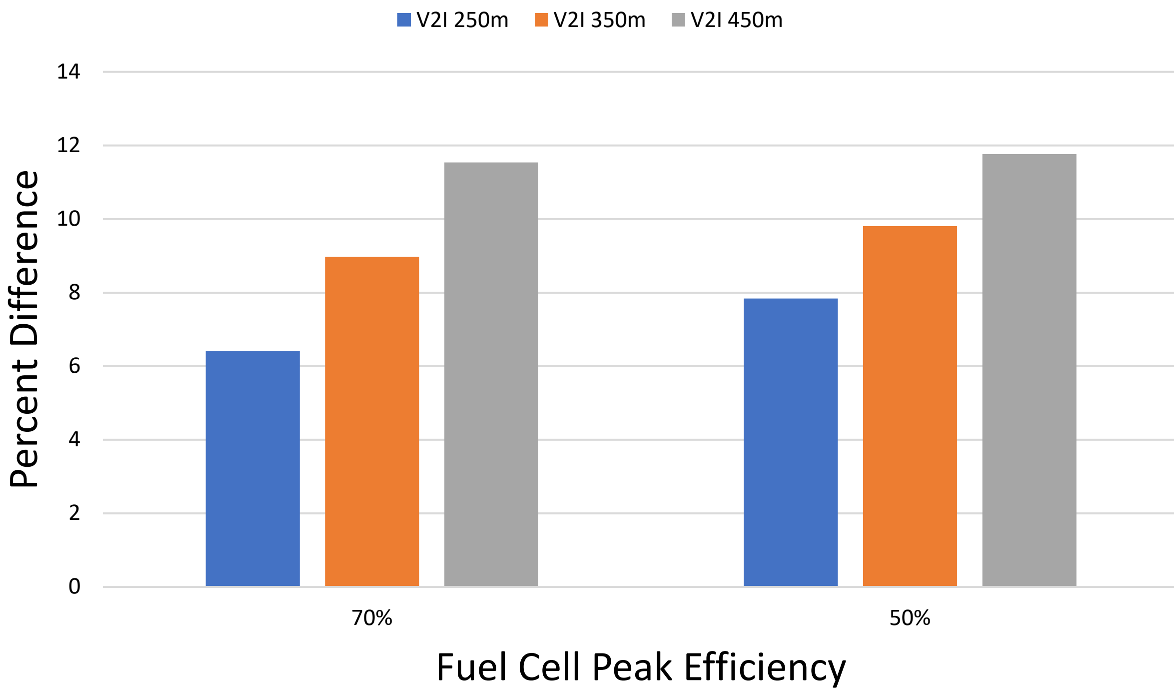

Figure 21. Toyota Mirai City Energy Improvements with Variations and Connectivity

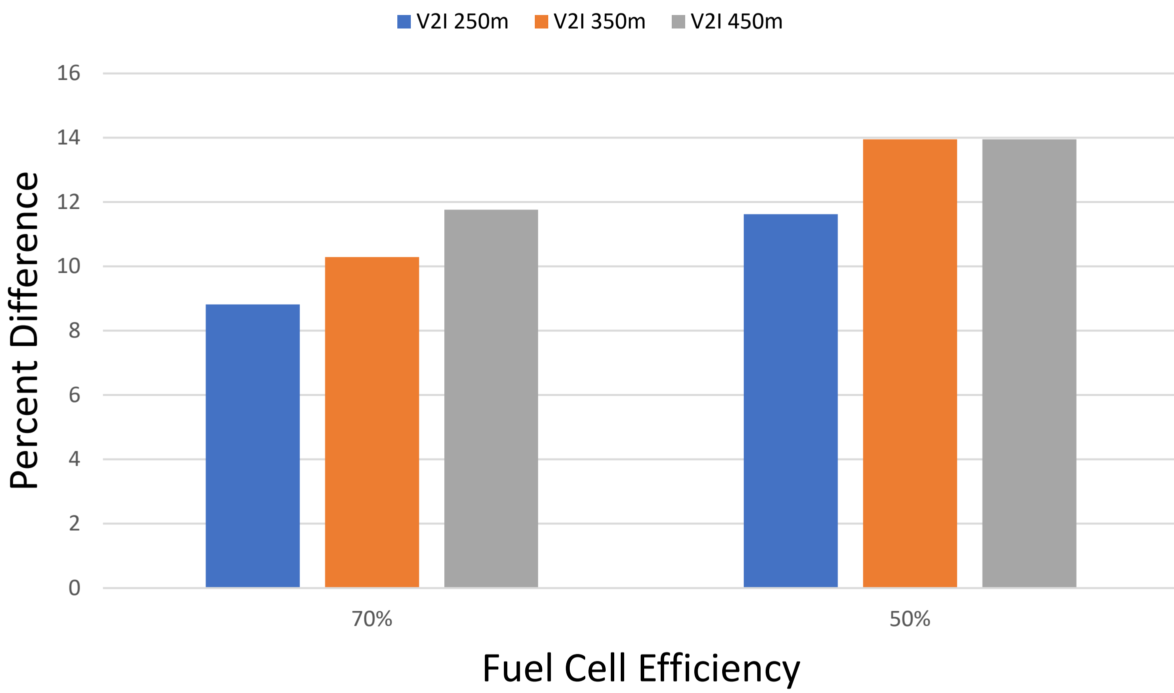

Figure 22. Hyundai Tucson City Energy Improvements with Variations and Connectivity

Figure 23 and Figure 24 show the percent improvement over the HWFET highway fuel economy due to V2X connectivity for each variation and vehicle model. Improvements ranged from 4% to 24% for the Toyota Mirai and 5% to 27% for the Hyundai Tucson. Linear improvements from platooning are also apparent: doubling the drag coefficient reduction nearly doubled the fuel economy improvement for each case.

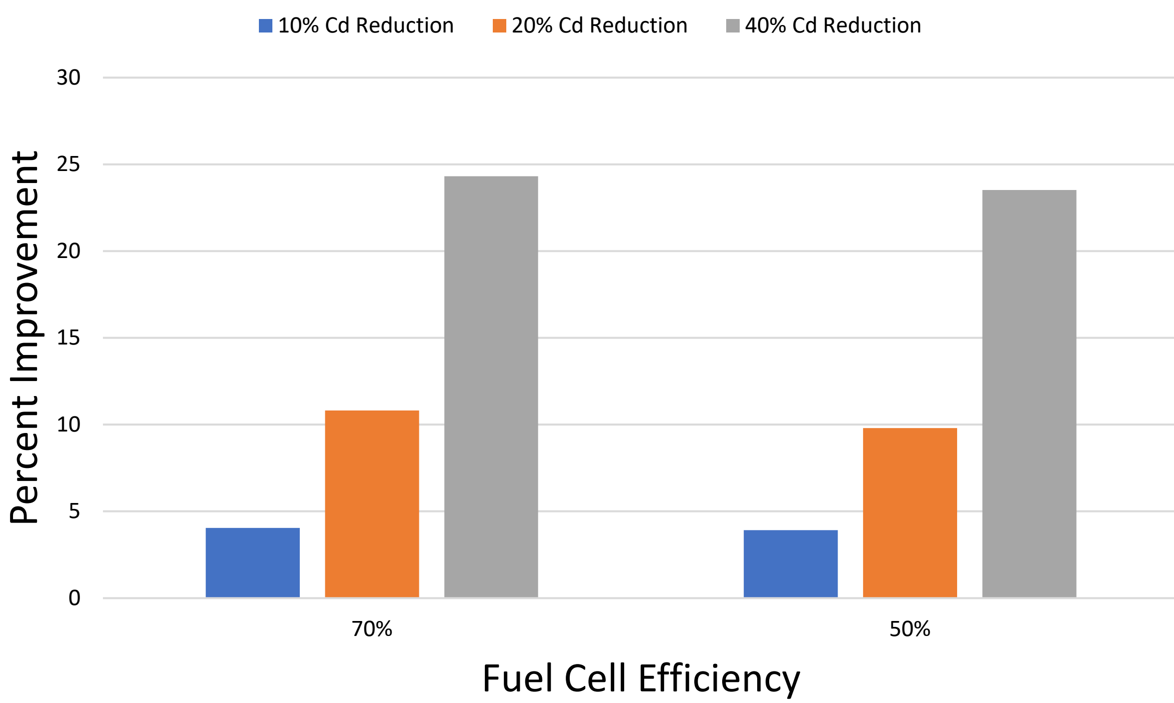

Figure 23. Toyota Mirai Highway Energy Improvements with Variations and Connectivity

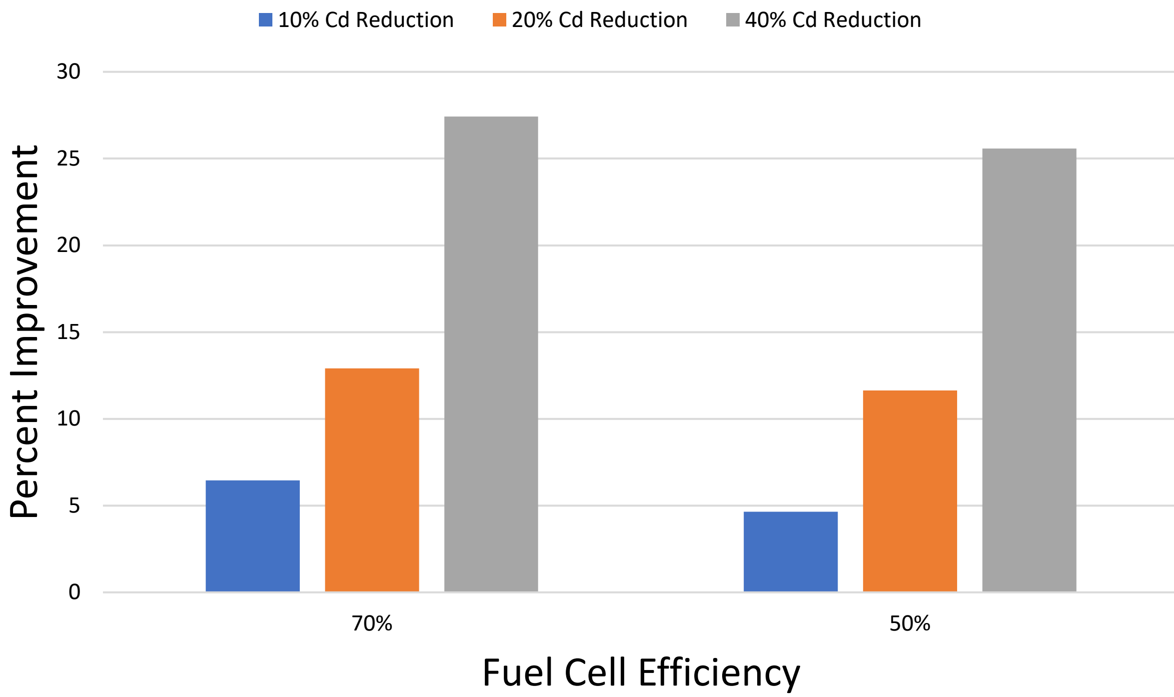

Figure 24. Hyundai Tucson Highway Energy Improvements with Variations and Connectivity

5.3 Connectivity Cost Savings

Fuel prices for operating each vehicle for a year were calculated for all simulation results discussed previously. Figure 25 and Figure 26 show the fuel prices for each vehicle in 2021 and 2035, respectively. Additional details are shown in Appendix A: Combined Fuel Economy through Appendix D: 2035 Low Fuel Prices. Because of high current day prices of hydrogen, the cost to operate a FCEV in 2021 is about four times as much as the cost to operate a BEV. Once hydrogen infrastructure matures and the price of hydrogen declines by 2035, the cost to operate a FCEV will only be about twice as much to operate than a BEV [90].

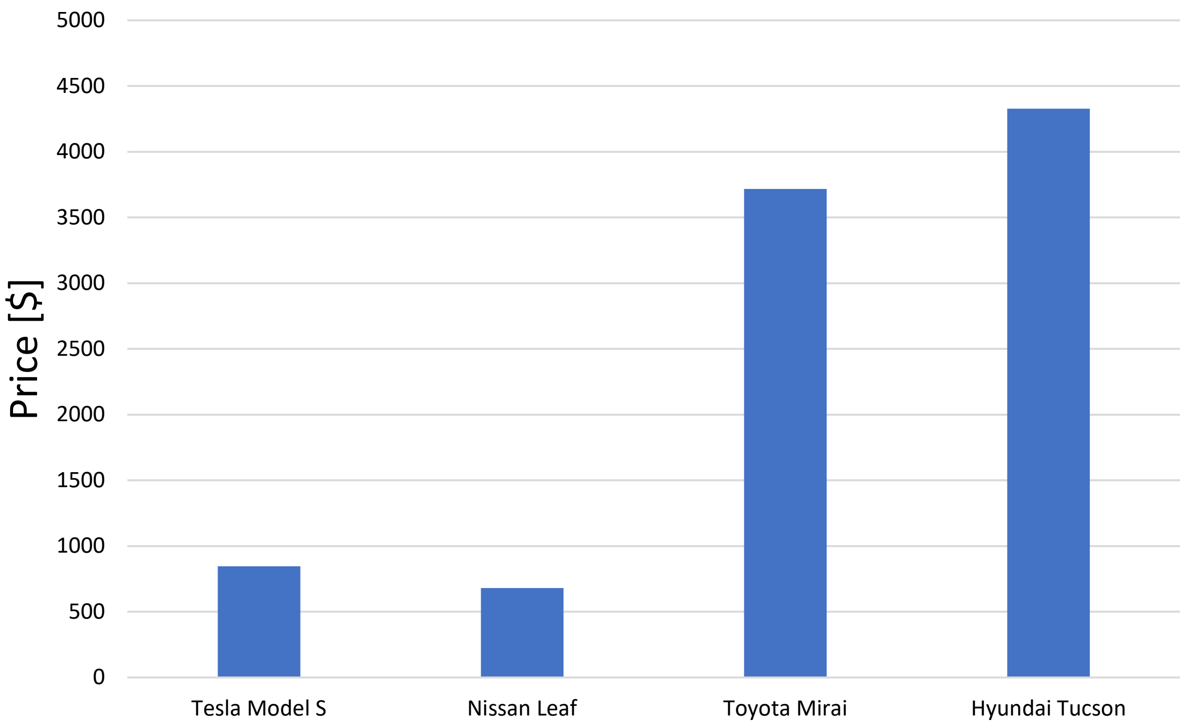

Figure 25. Annual Fuel Prices Without Connectivity, 2021

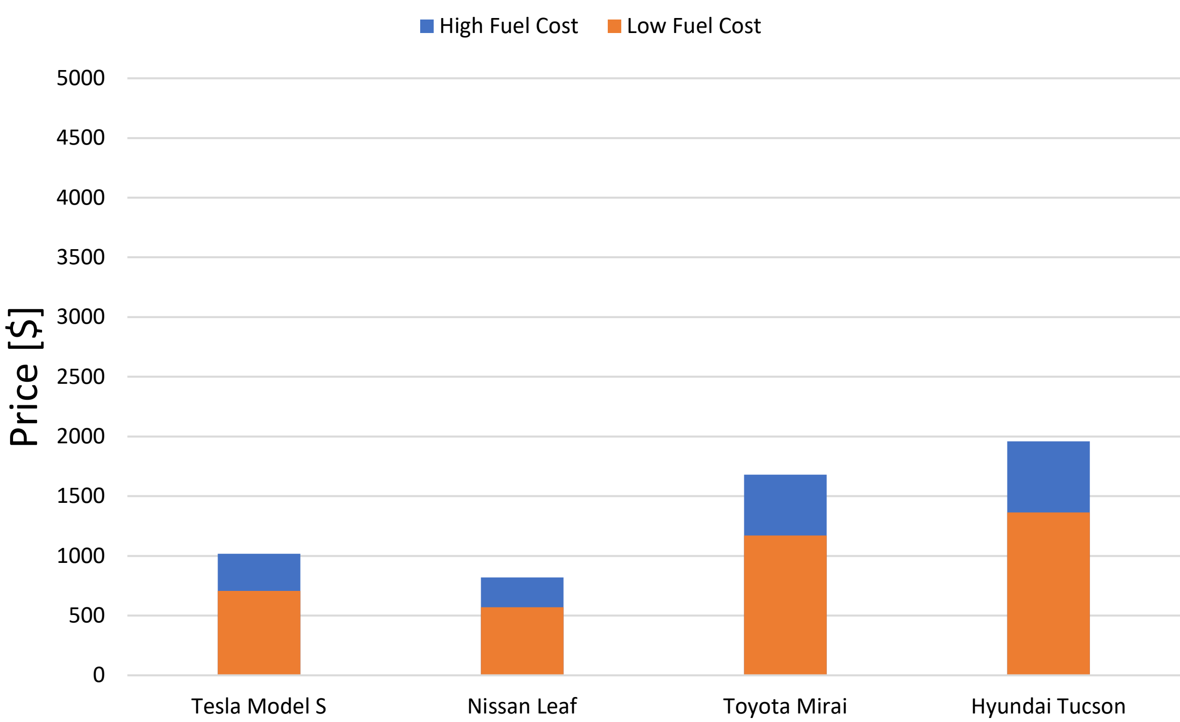

Figure 26. Annual Fuel Prices Without Connectivity, 2035

Today’s conventional gasoline powered vehicle that gets 27 MPG and travels 15,000 miles per year would cost about $2000 to operate in 2021 and $2200 to operate in 2035. In 2021, the cost to operate an ICEV was 130% to 190% more than a BEV and 50% less than a FCEV. In 2035, the cost to operate the same ICEV would be 119% to 290% more than a BEV and 14% to 90% more than a FCEV. The lower future prices for zero-emission fuels could incentivize consumers to adopt zero-emission technologies.

Figure 27 and Figure 28 show a range of fuel prices in 2021 and 2035, respectively, for each vehicle and variation tested. This range highlights the potential fuel costs vehicles could have with connectivity and powertrain component variations. For BEVs, fuel costs would be closer to the high side of the cost range due to the tested 97% and 100% roundtrip efficiency being unrealistic for real batteries. For FCEVs, the future fuel prices would be in the lower end of the price range due to the possibility that technological advances could increase fuel cell efficiency to 70%. Connected BEVs have the potential to save 6.2% in fuel, or $45 per year in 2021 and $55 per year in 2035 when travelling 15,00 miles per year. Connected FCEVs have the potential to save 5.7% in fuel, or $244 per year in 2021 and $93 per year in 2035 when travelling 15,000 miles per year.

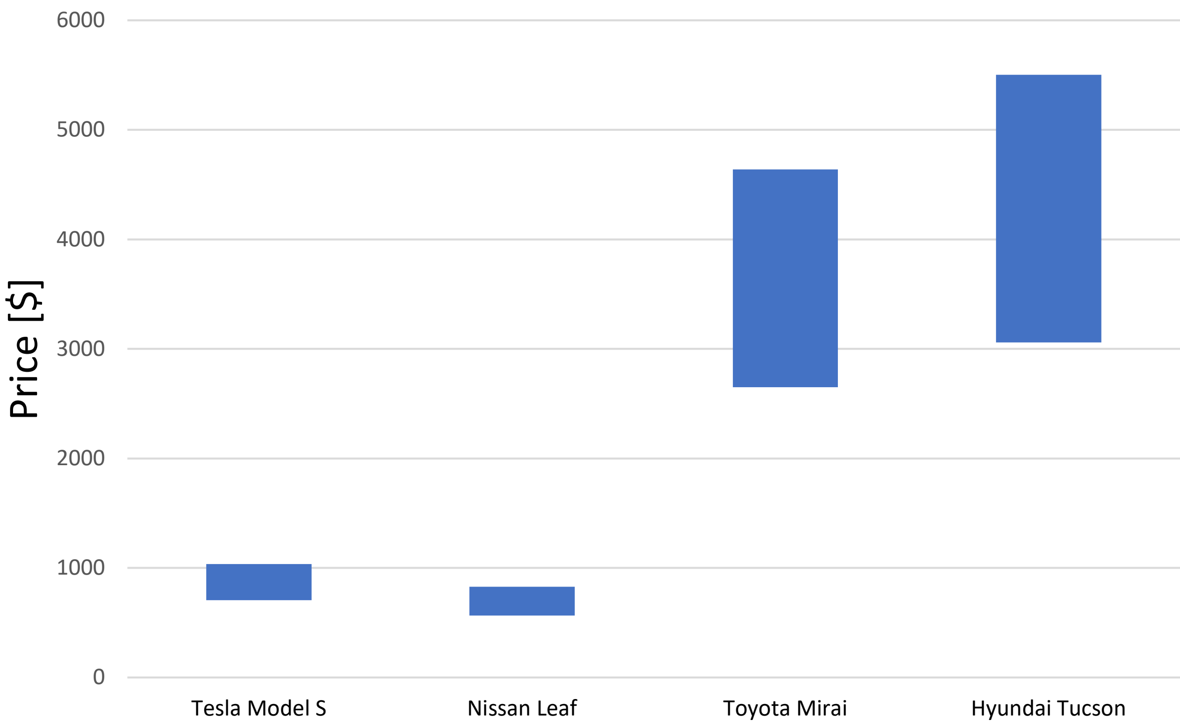

Figure 27. Fuel Price Range with Connectivity, 2021

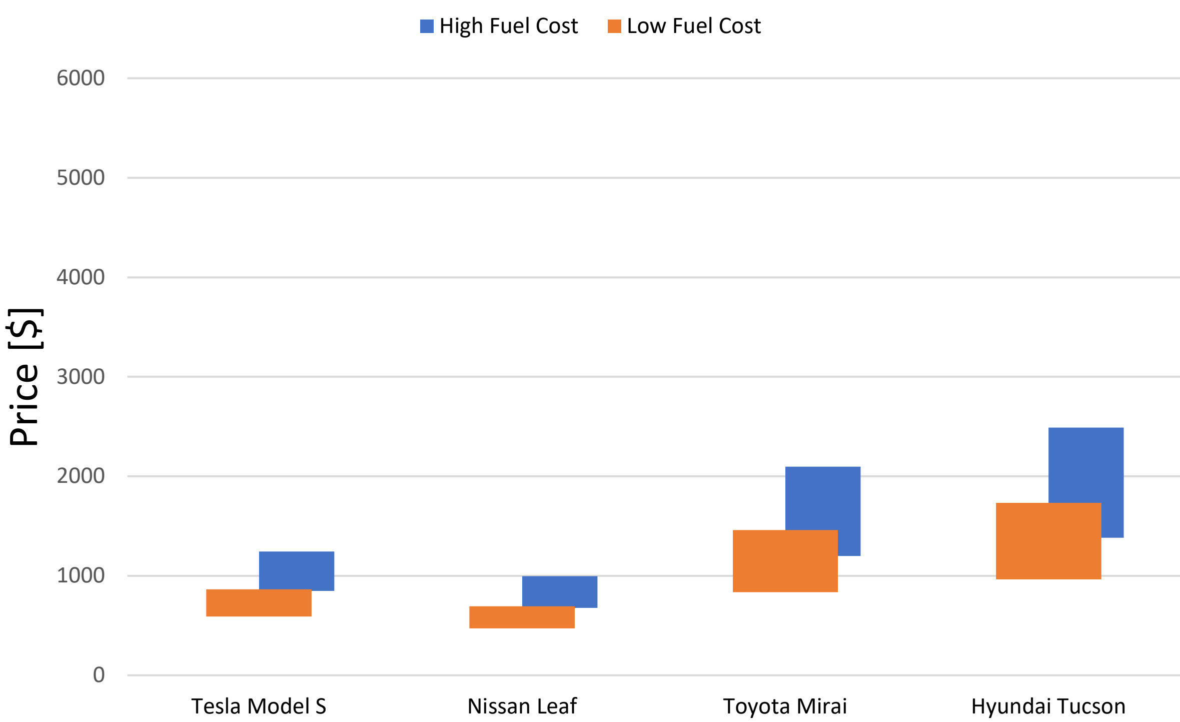

Figure 28. Fuel Price Range with Connectivity, 2035

6. SUMMARY and CONCLUSIONS

6.1 Summary

Social and political pressures derived from the growing awareness of transportation hazards and climate change are driving the evolution of transportation. While reducing vehicular accidents is one of the main goals of connected autonomy, this technology may also enable benefits for fuel economy. Additionally, the push for zero-emission technology will have the added benefit of replacing current systems with those that are more efficient. In anticipation of these changes, the fuel use impacts of zero-emission connected and autonomous mobility were analyzed to better inform consumers of the benefits of these technologies.

Vehicles equipped with CDA were analyzed in multiple scenarios to provide insight into how varying levels of connectivity could impact two important factors for consumers when purchasing a new vehicle: fuel economy and annual fuel expense. Fuel economy simulations were varied with more efficient powertrain components to reflect possible future improvements in vehicle technology. Annual fuel price estimations were conducted using forecasted fuel prices for 2035 to better reflect costs in a time where zero-emission and connected technologies will be more mature and deployed in greater quantities. The figures below show the key results of this study.

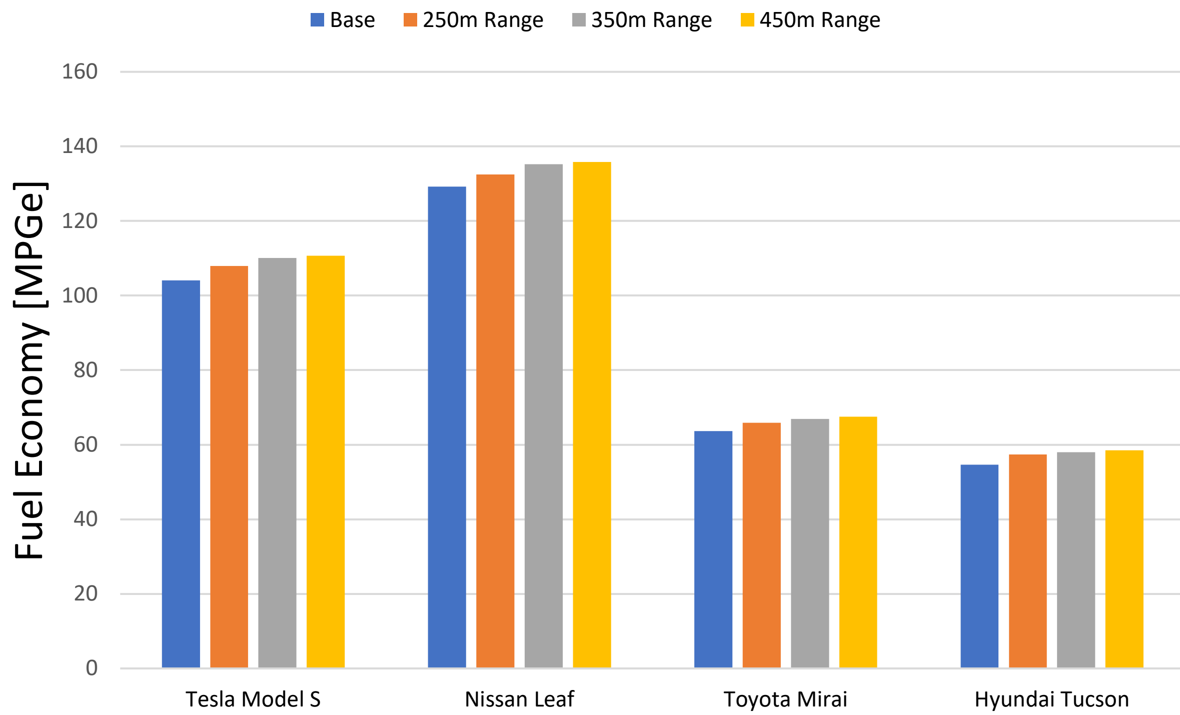

Figure 29. Combined Fuel Economy with Connectivity

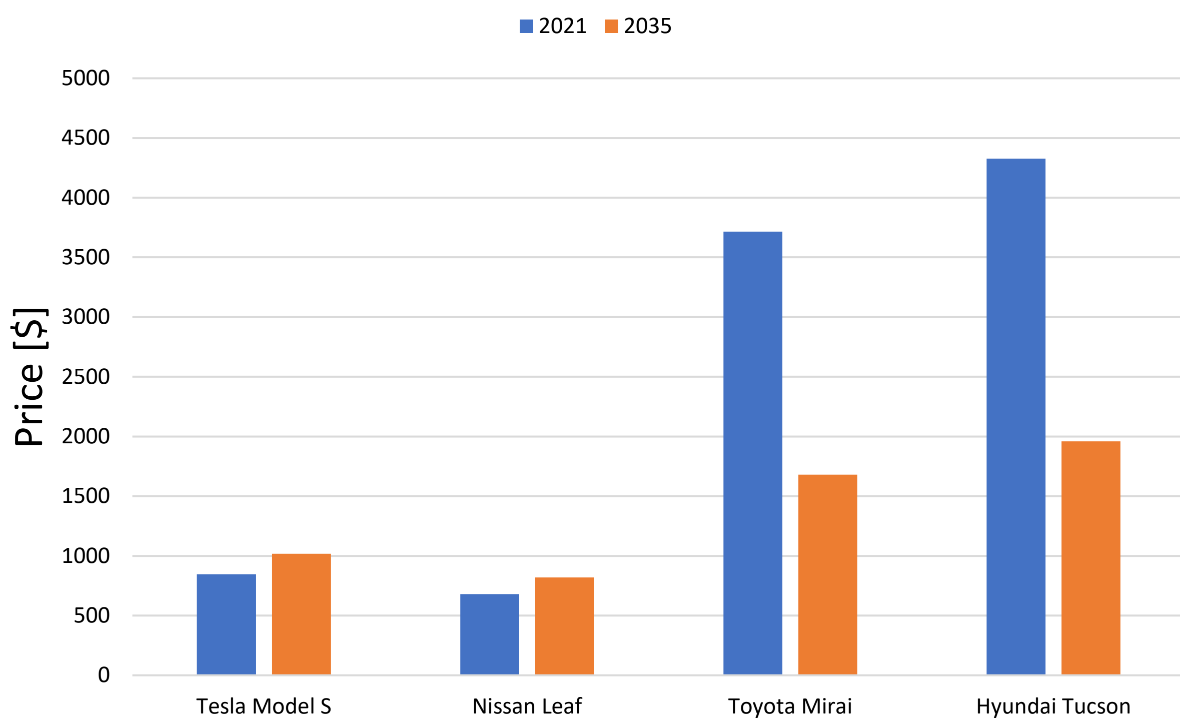

Figure 30. Annual Fuel Cost Without Connectivity

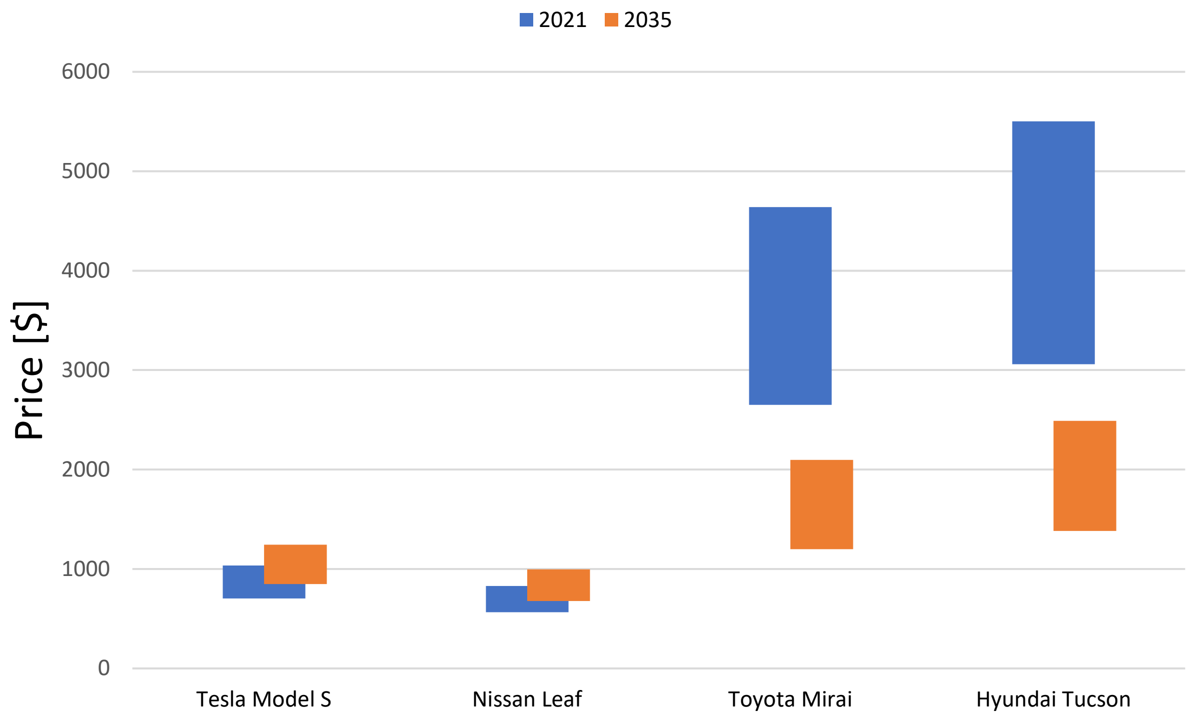

Figure 31. Annual Fuel Cost Range with Connectivity

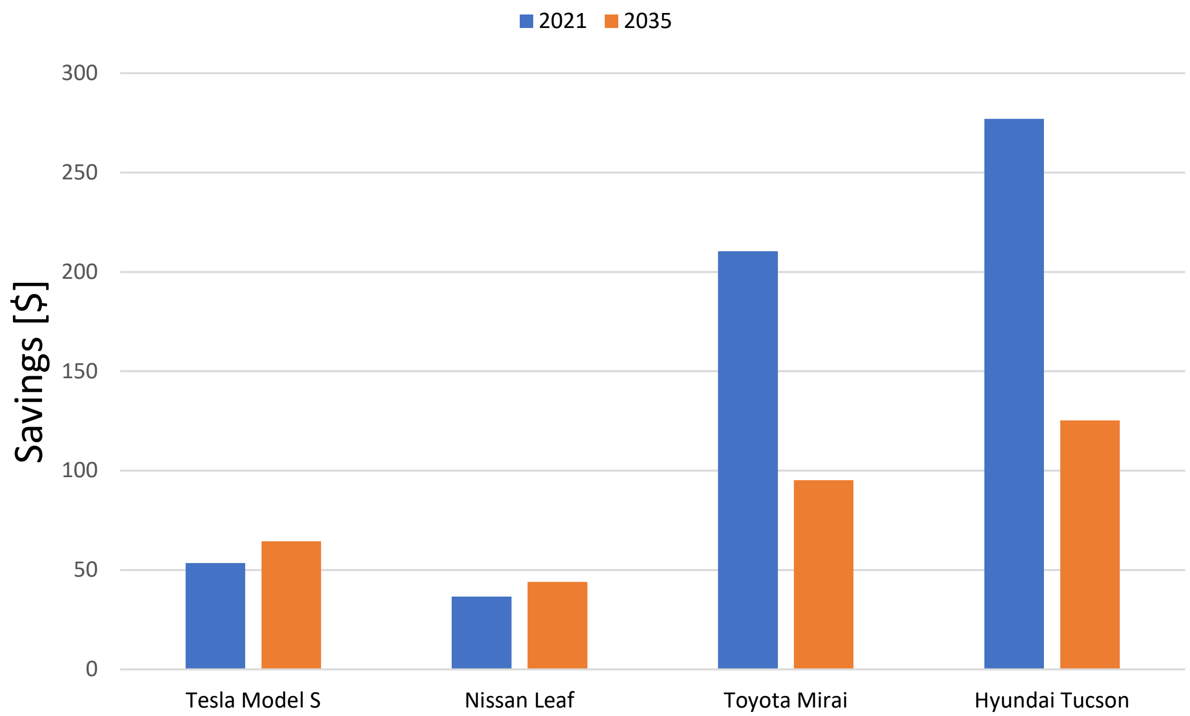

Figure 32. Average Annual Savings with Connectivity

Overall, the addition of connectivity improves fuel economy and decreases annual fuel costs. By equipping a vehicle with connectivity, the city fuel economy can improve by up to 13%, while highway fuel economy can improve by up to 32%. Furthermore, the combined fuel economy can improve by 18% with connectivity. When varying component efficiency, the relative improvement decreases with increasing component efficiency.

By 2035, the fuel cost to operate an ICV can be up to 290% more than a BEV and 90% more than a FCEV. The addition of connectivity to ZEVs s could achieve 6% in fuel savings. With a BEV and FCEV, average drivers could save \$55 and \$93 per year, respectively, with connectivity over the fuel cost of operating an ICV without CDA in 2035.

In closing, this thesis reveals that V2X connectivity will have a positive impact on energy usage for ZEVs. The growing popularity of zero-emission technology, as well as the combination of energy savings and possible safety improvements from connectivity make these advancements worthy for continued investment and development. Zero-emission connected and autonomous vehicles will be the next major step in the evolution of transportation.

6.2 Conclusions

- **Annual fuel costs will decrease with the introduction of V2X connectivity**

The fuel costs for each connected FASTSim vehicle models were calculated. With connectivity, BEVs are projected to gain 6.2% in fuel savings, while FCEVs are projected to gain 5.7% in fuel savings. For average drivers, this would amount to \$45 per year for BEVs and \$244 per year for FCEVs in 2021 and \$55 per year for BEVs and \$93 per year for FCEVs in 2035

- **Increasing the connectivity range above 350m for V2I results in diminishing returns in fuel economy improvement**

Each FASTSim vehicle model was tested with augmented FTP drive cycles at three ranges of connectivity: 250 meters, 350 meters, and 450 meters. All city tests, including the sensitivity analysis with varied component efficiencies, saw reduced improvements from connectivity when increasing the range from 350 meters to 450 meters. In these baseline tests, the percent improvement from 250 meters to 350 meters of connectivity ranged from 20% to 83%, while the percent improvement from 350 meters to 450 meters ranged from 9% to 17%.

- **Reducing drag coefficient with V2V platooning results in linear returns in fuel economy improvement**

When reducing the coefficient of drag for each FASTSim vehicle model by 10%, 20%, and 40%, all fuel efficiency gains were linearly related. In the base HWFET tests, doubling the drag coefficient reduction from 10% to 20% resulted in nearly doubling the fuel economy improvement from 6% to 11%. Further doubling the reduction from 20% to 40% also resulted in nearly doubling the fuel economy improvement from 11% to 26%. This effect was also seen in the varied component tests.

- **Higher efficiency components lead to lower fuel economy improvements from connectivity than vehicles with less efficient components**

The roundtrip efficiency of the traction battery for BEVs and the fuel cell efficiency for FCEVs were varied to determine how future changes in component efficiency could affect fuel usage in connected vehicles. In the city tests, the vehicles with more efficient components had lower gains in fuel economy due to connectivity than the vehicles with less efficient components.

- **Future fuel costs will further incentivize consumers to adopt zero-emission technologies**

The fuel prices of a current ICEV and various BEV and FCEV configurations were calculated for 2021 and 2035. BEVs have the lowest fuel prices in both years, with ICEV fuel prices being up to 190% and 290% higher for 2021 and 2035, respectively. The price to operate FCEVs was 50% more than the price for ICEVs in 2021. With maturing hydrogen infrastructure, the estimated cost to operate an ICEV in 2035 would be up to 90% more than operating a FCEV.

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Appendix A: Combined Fuel Economy
Tesla Model S

Combined MPGe, Base HWFET

Battery Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
100%	107	110	113	113
97%	104	108	110	111
75%	85	90	92	92

Combined MPGe, 10% C_d Reduction

Battery Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
100%	109	112	115	115
97%	107	111	113	113
75%	87	92	94	95

Combined MPGe, 20% C_d Reduction

Battery Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
100%	112	115	118	118
97%	109	113	115	116
75%	90	94	96	97

Combined MPGe, 40% C_d Reduction

Battery Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
100%	119	122	125	125
97%	116	120	122	122
75%	95	99	101	102

Nissan Leaf

Combined MPGe, Base HWFET

Battery Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
100%	132	136	138	138
97%	129	133	135	136
75%	106	111	113	114

Combined MPGe, 10% C_d Reduction

Battery Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
100%	135	139	142	142
97%	132	136	138	139
75%	109	114	116	117

Combined MPGe, 20% C_d Reduction

Battery Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
100%	140	143	146	146
97%	136	139	142	143
75%	112	117	119	120

Combined MPGe, 40% C_d Reduction

Battery Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
100%	149	153	155	156
97%	146	149	152	152
75%	120	125	127	128

Toyota Mirai

Combined MPGe, Base HWFET

Fuel Cell Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
70%	76	79	80	81
60%	64	66	67	68
50%	51	53	54	54

Combined MPGe, 10% C_d Reduction

Fuel Cell Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
70%	78	80	81	83
60%	65	68	69	69
50%	52	54	55	55

Combined MPGe, 20% C_d Reduction

Fuel Cell Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
70%	80	83	84	85
60%	67	69	70	71
50%	53	55	56	57

Combined MPGe, 40% C_d Reduction

Fuel Cell Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
70%	84	87	88	89
60%	71	73	74	75
50%	56	59	59	60

Hyundai Tucson

Combined MPGe, Base HWFET

Fuel Cell Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
70%	65	69	69	70
60%	55	57	58	59
50%	43	46	46	46

Combined MPGe, 10% C_d Reduction

Fuel Cell Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
70%	67	70	71	72
60%	56	59	59	60
50%	44	47	47	47

Combined MPGe, 20% C_d Reduction

Fuel Cell Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
70%	69	72	73	73
60%	57	60	61	61
50%	45	48	49	49

Combined MPGe, 40% C_d Reduction

Fuel Cell Efficiency	FTP MPGe	V2I 250m MPGe	V2I 350m MPGe	V2I 450m MPGe
70%	73	76	77	77
60%	61	64	64	65
50%	48	51	51	51

Appendix B: 2021 Fuel Prices
Tesla Model S

Base Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	830	800	780	780
97%	850	820	800	800
75%	1000	980	960	954

10% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	810	790	770	770
97%	820	800	780	780
75%	1000	960	940	930

20% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	790	760	750	750
97%	810	780	770	760
75%	980	940	920	910

40% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	740	720	710	710
97%	760	740	720	720
75%	930	890	870	870

Nissan Leaf

Base Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	670	650	640	640
97%	680	660	650	6560
75%	830	800	780	770

10% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	650	630	620	620
97%	660	650	640	630
75%	810	770	760	750

20% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	630	610	600	600
97%	650	630	620	620
75%	780	750	740	730

40% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	890	570	570	560
97%	600	590	580	580
75%	730	710	700	790

Toyota Mirai

Base Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	3104	2996	2955	2915
60%	3717	3592	3533	3505
50%	4638	4447	4401	4356

10% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	3050	2946	2906	2867
60%	3614	3497	3441	3413
50%	4558	4373	4329	4285

20% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	2964	2866	2828	2791
60%	3541	3428	3375	3348
50%	4442	4266	4224	4183

40% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	2806	2717	2684	2650
60%	3339	3238	3190	3166
50%	4194	4037	3999	3962

Hyundai Tucson

Base Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	3623	3448	3421	3394
60%	4329	4121	4082	4044
50%	5501	5171	5109	5109

10% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	3525	3360	3334	3308
60%	4224	4026	3989	3952
50%	5389	5071	5012	5012

20% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	3433	3276	3252	3227
60%	4125	3936	3900	3865
50%	5228	492	4872	4872

40% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	3243	3102	3080	3058
60%	3881	3714	3682	3651
50%	4933	4666	4616	4616

Appendix C: 2035 High Fuel Prices

Tesla Model S

Base Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	990	960	940	940
97%	1000	980	960	960
75%	120	1200	1200	1100

10% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	970	940	920	920
97%	990	960	940	930
75%	1200	1200	1100	1100

20% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	940	920	900	900
97%	970	940	920	920
75%	1200	1100	1100	1100

40% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	890	870	850	850
97%	910	880	870	870
75%	1100	1100	1000	1000

Nissan Leaf

Base Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	800	780	770	770
97%	820	800	780	780
75%	1000	960	940	930

10% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	780	760	750	740
97%	800	780	760	760
75%	970	930	910	900

20% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	760	740	730	720
97%	780	760	750	740
75%	940	900	890	880

40% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	710	690	680	680
97%	730	710	700	690
75%	880	850	840	830

Toyota Mirai

Base Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1400	1360	1340	1320
60%	1680	1630	1600	1590
50%	2100	2010	1990	1970

10% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1380	1330	1310	1300
60%	1640	1580	1560	1540
50%	2060	1980	1960	1940

20% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1340	1300	1280	1260
60%	1600	1550	1530	1510
50%	2010	1930	1910	1890

40% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1270	1230	1210	1200
60%	1510	1460	1440	1430
50%	1900	1830	1810	1790

Hyundai Tucson

Base Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1640	1560	1550	1540
60%	1960	1860	1850	1830
50%	2490	2340	2310	2310

10% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1590	1520	1510	1500
60%	1910	1820	1800	1790
50%	2440	2290	2270	2270

20% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1550	1480	1470	1460
60%	1870	1780	1760	1750
50%	2370	2230	2200	2200

40% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1470	1400	1390	1380
60%	1760	1680	1670	1650
50%	2230	2110	2090	2090

Appendix D: 2035 Low Fuel Prices

Tesla Model S

Base Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	690	670	650	650
97%	710	680	670	670
75%	870	820	800	800

10% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	680	660	640	640
97%	690	670	650	650
75%	840	800	780	780

20% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	660	640	620	620
97%	680	650	640	640
75%	820	780	770	760

40% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	620	600	590	590
97%	640	620	600	600
75%	780	740	730	720

Nissan Leaf

Base Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	560	540	530	530
97%	570	560	540	5440
75%	690	670	650	640

10% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	540	530	520	520
97%	560	540	530	530
75%	670	650	640	630

20% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	530	510	510	500
97%	540	530	520	520
75%	650	630	620	610

40% C_d Reduction Price

Battery Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
100%	490	480	470	470
97%	500	490	480	480
75%	610	590	580	580

Toyota Mirai

Base Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	977	943	930	918
60%	1170	1130	1110	1100
50%	1460	1400	1390	1370

10% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	960	928	915	903
60%	1140	1100	1080	1070
50%	1440	1380	1360	1350

20% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	933	902	890	879
60%	1120	1080	1060	1050
50%	1400	1340	1330	1320

40% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	884	856	845	835
60%	1050	1020	1000	997
50%	1320	1270	1260	1250

Hyundai Tucson

Base Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1140	1090	1080	1070
60%	1360	1300	1290	1270
50%	1730	1630	1610	1610

10% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1110	1060	1050	1040
60%	1330	1270	1260	1240
50%	1700	1600	1580	1580

20% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1080	1030	1020	1020
60%	1300	1240	1230	1220
50%	1650	1550	1530	1530

40% C_d Reduction Price

Fuel Cell Efficiency	FTP Price	V2I 250m Price	V2I 350m Price	V2I 450m Price
70%	1020	977	970	963
60%	1220	1170	1160	1150
50%	1550	1470	1450	1450