Title
Zero Emission Shared-Use Autonomous Vehicles: A Deployment Construct and Associated Energy Grid and Environmental Impacts

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Publication Date
2019

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA,
IRVINE

Zero Emission Shared-Use Autonomous Vehicles:
A Deployment Construct and Associated Energy Grid and Environmental Impacts

DISSERTATION

submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in Mechanical and Aerospace Engineering

by

Van Thomas Wifvat

Dissertation Committee:
Professor Scott Samuelsen, Chair
Dean Gregory Washington
Professor Stephen Ritchie

2019

DEDICATION

Paraphrased from my final lab meeting, November 22nd, 2019:

"As some of you may know, I didn't pass my prelim exam the first time. You only get two chances to pass, so I had just one final chance to re-take and pass to stay in the program. During this study period I started a gratitude journal. I wrote down three things I was grateful for each night before going to bed in a plain, unassuming notebook. It could be gratitude for something as simple as a fun conversation that day, or for having nice weather. Or as was ultimately the case, something as big as finally passing the prelim. I started the journal because I was told that this practice would help me stay positive and help me stay open to the many opportunities each day offers regardless of how I may be feeling about my current situation. I found this to be true and deeply valuable.

But what I wasn't told, was how after some time you can flip through the pages of this journal and see patterns of what you are grateful for. Days, weeks, months, years – of what really matters to you. What is obvious from my pages is how important this lab this has been in my life. I have been provided with some of my greatest challenges over the past five years, and at the same time, I've been bolstered by the support of truly brilliant and kind people. I've learned and grown far more than I could have imagined, all thanks to this special community we share. It's been an honor to call you my friends and colleagues. As my final and possibly insurmountable challenge, I must pay this experience forward. Thank you all so much."

This work is dedicated to the many people in that plain, unassuming notebook.

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NOMENCLATURE

AFV	Alternatively Fueled Vehicle
BEV	Battery Electric Vehicle
Caltrans	California Department of Transportation
CAMP	Crash Avoidance Metrics Partnership
CAP	Criteria Air Pollutant
CAV	Connected and Autonomous Vehicle
CS	Camera System
CSTDM	California Statewide Travel Demand Model
CVIS	Cooperative Vehicle Infrastructure Systems
DIAMANT	Dynamic Information and Application for Mobility with Adaptive Networks and Telematics Infrastructure
EMFAC	Emissions Factor
EMIT	Emissions from Traffic
FASTSim	Future Automotive Systems Technology Simulator
FETCH	Fuel Economy and Traffic of Connected Hybrids
FCW	Forward Collision Warning systems
GHG	Greenhouse Gas
GREET	Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation
H2V	Human to Vehicle
HEV	Hybrid Electric Vehicle
HWFET	Highway Fuel Economy Driving Schedule
ICV	Internal Combustion Vehicle
ITN	Intelligent Transit/Transportation Network
LDV	Light Duty Vehicle

LDW	Lane Departure Warning systems
NHTSA	National Highway Traffic Safety Administration
NREL	National Renewable Energy Laboratory
OMNET++	Objective Modular Network Testbed in C++
PHEV	Plugin Hybrid Electric Vehicle
SAV	Shared Autonomous Vehicle
SAEV	Shared Autonomous Electric Vehicle
SDPTM	Short Distance Personal Travel Model
SUMO	Simulation of Urban Mobility
UDDS	Urban Dynamometer Driving Schedule
US	United States
USDoT	United States Department of Transportation
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
V2X	Vehicle to Vehicle / Vehicle to Infrastructure
VRS	Vehicular Radar System

ACKNOWLEDGEMENTS

When people ask me how I found the right graduate school, I tell them that I didn't look for the right school. I looked for, and found, the right advisor. I know in my heart as much as my mind that I made the perfect choice. You have set the bar so high as an engineer, an academic, and as an honorable human being (and the list could go on and on). I know you feel that it's just all part of the job, and that thanks are totally unnecessary, but Professor Samuelsen: Thank you.

Thank you to my graduate student colleagues. I still cannot believe how lucky I have been to work alongside you. You've been there by my side at each step of the way. You answered my questions for hours over the phone when I was still a prospective student in Minnesota. It turns out that this was foreshadowing of all the help you've given me over the last five years. Technical help just being a part of it all. I will always look back on our conversations, lunch outings, camping trips, and yes even some of the tough times – with a smile.

Thank you to my undergraduate research assistants. You are amazing researchers and I know that you have very bright futures ahead of you. Serving as your mentor has been one of the most rewarding experiences of my life. Please know that I will continue paying it all forward.

Thank you to Marie. Your love and support allowed me to thrive during the creation of this work. You are my secret weapon. You are my best friend. Love you!

CURRICULUM VITAE

EDUCATION

2019 **Ph.D., Mechanical and Aerospace Engineering**
University of California, Irvine
Advisor: Professor Scott Samuelsen
Dissertation: "Zero Emission Shared-Use Autonomous Vehicles: A Deployment Construct and Associated Energy Grid and Environmental Impacts"

2016 **M.S., Mechanical and Aerospace Engineering**
University of California, Irvine
Advisor: Professor Scott Samuelsen
Thesis: "A Planning Tool to Assess Advanced Vehicle Sensor Technologies on Traffic Flow, Fuel Economy, and Emissions"

2013 **B.S., Mechanical Engineering,** Cum Laude
University of Saint Thomas, Saint Paul, MN

PROFESSIONAL APPOINTMENTS AND EXPERIENCE

2014-2019 **Graduate Student Researcher**
Department of Mechanical and Aerospace Engineering – UC Irvine, CA
- Developed simulation framework for the measurement of advanced vehicular technology on fuel economy, traffic flow, and emissions
- Led collaborative research project with major automaker, investigating fuel efficiency and emissions impacts of integrating advanced sensor technologies on future vehicles
- Honed interpersonal and research aptitude skills with industry research collaborations

2016, 2019 **Writer**
National Public Radio (NPR) – Pasadena, CA
- Selected to join the first team of student writers for Sandra Tsing Loh's "The Loh Down on Science"
- Honed scientific communication skills by condensing scientific articles into fun and engaging radio-friendly segments.
- Volunteered to serve as first managing editor for student peers, scheduled team meetings and organized our efforts using Google Drive.

2016, Summer **Engineering Co-Op**
Toyota Motors North America, Inc. – Ann Arbor, MI
- Conducted research in the Hybrid Vehicles and Drivetrain Division, developed simulation tools to evaluate integration of future sensor technologies
- Assisted in evaluating prototype vehicle performance in U.S. suitability testing

2012-2014 **Technical Aide**
3M Company – Maplewood, MN
- Conducted research in the 3M Corporate Research Process Lab Division, worked on projects that integrate recycled/bio-renewable materials into existing product lines, test energy-saving methods to improve current manufacturing processes of nonwoven materials
- Designed and implemented research equipment, professional experience using the CAD software package SolidWorks
- Applied the scientific method in collaboration with laboratory technicians, division engineers, and corporate scientists of various seniority and discipline

2011-2012 **Research Assistant**

University of Saint Thomas – St. Paul, MN

- Presented at 2012 ASME IMECE Conference, Houston TX
- Gained hands-on research experience on both microfiltration and micromachining projects

AWARDS & FELLOWSHIPS

2019	Finalist: California Council on Science and Technology (CCST) Policy Fellowship
2019	Nominated: Mechanical and Aerospace Engr. Graduate Student of the Year
2018	Outstanding Oral Presentation Award, Society of Automotive Engineers
2016	Association of Energy Engineers Scholarship, AEE Southern California
2015	Association of Energy Engineers Scholarship, AEE Southern California

PEER-REVIEWED ACADEMIC JOURNAL PUBLICATIONS

Wifvat, V., Shaffer, B., and Samuelsen, S. (2018), "A Review of Sensor Technologies for Automotive Fuel Economy Benefits", *SAE International Journal of Connected and Automated Vehicles.* DOI: 10.4271/12-02-01-0001

Tarroja B., Zhang, L., **Wifvat, V.**, Shaffer, B., Samuelsen, S. (2016), "Assessing the Stationary Energy Storage Equivalency of Vehicle-to-Grid Charging Battery Electric Vehicles", *Energy,* DOI: 10.1016/j.energy.2016.03.094

PUBLICATIONS UNDER-REVIEW

Asher, Z., **Wifvat, V.**, Patil, A., Bradley, T., Samuelsen, S., Frank, A., (*pending minor revisions*), "The Importance of HEV Fuel Economy and Two Research Gaps Preventing Real World Implementation of Optimal Energy Management", *SAE International Journal of Alternative Powertrains*

REFEREED CONFERENCE PUBLICATIONS

Wifvat, V., Shaffer, B., and Samuelsen, S. (2018, April), "A Planning Tool to Assess Advanced Vehicle Sensor Technologies on Traffic Flow, Fuel Economy, and Emissions", *SAE WCX: World Congress Experience 2018*, Detroit, MI, DOI: 10.4271/2018-01-1100

Asher, Z., **Wifvat, V.**, Navarro, A., Samuelsen, S., Bradley, T. (2017, January), "The Importance of HEV Fuel Economy and Two Research Gaps Preventing Real World Implementation of Optimal Energy Management", *SAE Symposium on International Automotive Technology 2017 Proceedings*, Maharashtra, India, DOI: 10.4271/2017-26-0106

Nevala, S., **Wifvat, V.** Johnson, S., Wentz, J. (2012, November), "Relative Effects of Cooling and Lubrication in Micro-Milling of Aluminum and the Design of Atomization Cooling and Lubrication Systems", *ASME International Mechanical Engineering Congress and Exposition, 2012 Proceedings,* Houston, TX, DOI: 10.1115/IMECE2012-87825

INVITED TALKS

Wifvat, V. (2019, March). *Autonomous Vehicles and Microgrids.* Invited presentation at the ICEPAG 2019 Microgrid Global Summit, UC Irvine, CA.

Wifvat, V. (2018, September). *Autonomous Vehicles: Energy and Environmental Considerations.* Invited presentation at the Association of Energy Engineers Southern California Annual Conference, Downey, CA.

Wifvat, V. (2018, September). *Autonomous Vehicles: Energy and Environmental Considerations.* Invited presentation at the Atmospheric Integrated Research- UC Irvine (AIR-UCI) Conference, Lake Arrowhead, CA.

Wifvat, V. (2014, September). *Autonomous Vehicles.* Invited presentation at the Atmospheric Integrated Research- UC Irvine (AIR-UCI) Conference, Lake Arrowhead, CA.

OUTREACH PRESENTATIONS & WORKSHOPS

Wifvat, V. (2019, July). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to engineers from Korea Electric Power Corporation (KEPCO), UC Irvine, CA.

Jaimes, J., Wifvat, V.**,** Pullés, S., (2019, May). *Know-How Sessions: How to Write a Statement of Purpose & How to Fund Graduate School.* Served as part of a panel series given to underrepresented undergraduate students, UC Irvine, CA.

Wifvat, V., Lane, B., Matthews, B., Wang, S., (2019, May). *What is Engineering? Career and Education Guide from High school to PhD.* Presentation given to 8th grade science students at local public middle school. Presentation shared insight from diverse group of engineering PhD students, and hands-on demonstrations to help understand renewable energy technologies, Plaza Vista School, Irvine, CA.

Wifvat, V. (2019, May). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to undergraduate students taking a UC Irvine Sustainability Seminar Series, UC Irvine, CA.

Wifvat, V. (2019, February). *Sustainable Transportation Options.* Presentation given to engineers and management visiting from HORIBA Instruments, Inc., UC Irvine, CA.

Wifvat, V. (2018, December). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to undergraduate engineering students visiting from Dalian University, UC Irvine, CA.

Wifvat, V. (2018, November). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to undergraduate engineering students visiting from Soka University, UC Irvine, CA.

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Wifvat, V. (2018, August). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to undergraduate engineering students visiting from King Abdullah University of Science and Technology, UC Irvine, CA.

Wifvat, V. (2018, August). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to high school students taking part in the California State Summer School for Mathematics & Science (COSMOS) Program, UC Irvine, CA.

Wifvat, V., Lane, B., Novoa, L., Jaimes, D., Silverman, R., (2018, April). *Renewable Energy!* Hands-on renewable energy technology demonstrations in disadvantaged community for elementary school children in afterschool lesson, Oak View Family Resource Center, Huntington Beach, CA.

Wifvat, V., Lane, B., Asghari, M., Wang, S., (2018, April). *What is Engineering? Career and Education Guide from High school to PhD.* Presentation given to 6th grade science students at local public middle school. Presentation shared insight from diverse group of engineering PhD students, and hands-on demonstrations to help understand renewable energy technologies, Bonita Canyon Elementary School, Irvine, CA.

Wifvat, V. (2018, February). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to undergraduate students taking a UC Irvine Sustainability Seminar Series, UC Irvine, CA.

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Wifvat, V. (2017, August). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to undergraduate engineering students visiting from King Abdullah University of Science and Technology, UC Irvine, CA.

Wifvat, V. (2017, August). *Autonomous Vehicles: Energy and Environmental Impacts.* Presentation given to underrepresented students taking part in the Office of Access and Inclusion's Scholars Program, UC Irvine, CA.

OTHER OUTREACH & MENTORING

2014-2019 Irvine Unified School District: Science Project Helper, Judge, and STEM Advocate

2017 Moderator, Symposium for Graduate Research at UC Irvine

2015 Orange County Regional Science Fair Judge

TEACHING EXPERIENCE

2018 **Teaching Assistant** Sustainable Energy Systems,
Dr. Brian Tarroja
Student evaluations (*N*=16/20 Students): Mean Quality Rating: 3.85/4 (96.25%)
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SERVICE

2016-2019 **Graduate Student Representative**
School of Engineering
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2018 **Voting Member**
Student Health Insurance Advisory Council
University of California, Irvine

2014-2019 **Vice President of Outreach** Association of Energy
Engineers Student Chapter
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American Society of Mechanical Engineers
Society of Automotive Engineers

ABSTRACT OF DISSERTATION

Zero Emission Shared-Use Autonomous Vehicles:

A Deployment Construct and Associated Energy Grid and Environmental Impacts

By

Van Thomas Wifvat

Doctor of Philosophy in Mechanical and Aerospace Engineering

University of California, Irvine, 2019

Professor Scott Samuelsen, Chair

For decades, the leading cause of death for American youth has been the car accident, and the largest source of domestic Greenhouse Gas (GHG) and many Criteria Air Pollutants (CAPs) has been the transportation sector. The advent of the autonomous vehicle in combination with Battery-Electric Vehicles (BEVs) and Fuel-Cell Electric Vehicles (FCEVs) presents an opportunity to transcend both pernicious challenges. In particular, the evolution of safer and more efficient autonomous (i.e., robotic) driving behavior via vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, increased use of electric vehicles, and greater access to affordable and convenient shared (i.e., pooled) rides portend societal benefits including a significant reduction in energy demand and associated pollution. This dissertation evaluates the impact of Shared Autonomous Electric Vehicles (SAEVs, "Saves") on the California energy grid, GHG emissions, and CAPs.

Vehicle-centric impacts (i.e., efficiency changes due to vehicle design and driving behavior) are measured using a vehicle design tool together with a microscopic traffic simulation model to (1) design prototype SAEVs, and (2) measure their energy efficiency for standard and eco-driving scenarios and an array of performance characteristics (e.g., different electric drivetrains, various

communication protocols, etc.). Fleet-centric impacts (i.e., changes to vehicle allocation and usage) are measured using ArcGIS with a Caltrans travel demand model dataset to allocate and size SAEV stations, where SAEVs recharge/refuel and are sent to serve nearby trips in a hypothetical SAEV-deployment construct. The Holistic Energy Grid modelling tool (HiGRID) is used to measure SAEV impacts on the California electric grid and grid GHG and CAPs. The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model (GREET) is used to measure corresponding transportation sector GHG and CAP impacts.

Vehicle-centric energy impacts from SAEV-enabled eco-driving and platooning averaged net efficiency improvements of approximately 6-18%. Fleet-centric impacts include VMT changes from -11% to +36%, largely depending on ridesharing. Depending on SAEV design and operation, over 375,000 metric tons of annual CO_2-equivalent GHG emissions could be reduced by adopting the proposed SAEV-deployment construct in lieu of the projected conventionally-driven vehicle fleet. Corresponding CAP impacts include a net reduction of over 250 metric tons of annual NO_x emissions.

1. Introduction

1.1 Motivation

The leading cause of death for Americans between four and twenty-four years old is the car accident, and nearly 100 Americans die in car accidents every single day [1]. A medium sized jet aircraft holds approximately 100 people. Therefore, essentially a plane-crash equivalent of automobile fatalities occurs every day in the United States (U.S.). Such is the scale of tragedy on U.S. roadways.

Where do autonomous vehicles fit in? The vast majority of car accidents, approximately ninety-four percent, are caused by errors in human judgement [2]. The most common error in human judgement that leads to a general traffic accident is driver distraction, and the most common human error leading to a fatal traffic accident is drunk driving [3]. Such preventable mistakes in human judgement provoke the question: Could it be possible to transcend the responsibility placed on humans for driving? That is, could robots ultimately be responsible for a safe decision-making on our roads?

The answer is becoming “yes.” Recent progress in the development of the autonomous vehicle (AV) is demonstrated by numerous private companies. Consider the Google Autonomous Vehicle project and the associated Google subsidiary Waymo. In 2010, near the beginning of Waymo’s on-road testing, their AV was able to safely travel 5 miles before a human would have to intervene and to take control once again. This was five miles of safe, robotic driving on everyday roads and in everyday driving situations. Though not far distance, it was a start. In 2012, just two years later, their AV was able to travel 1000 miles before the human needed to take control. Essentially, their AV could use about two or three tanks of gas before requiring a human to intervene. Two years later, in 2014, it was reported that the Google AV system across a fleet of 24 vehicles (not for one single vehicle) was able to safety travel for a continuous 50,000 miles with no human input. The average American drives about 10,000 miles in one year, meaning that Google's AV could safety travel the equivalent mileage of five years of human travel. One hopes for better driving than to get into a serious car accident every five years, but the improvement to AV driving competency is getting clearer each year. Since then, Waymo has conducted a demonstration of their AVs in Arizona, where in 2017 members of the public have been able to use AVs from certain pickup and drop-off locations (though safety drivers are typically behind the wheel in case of a safety concern.).

Roadway accidents aside, another safety priority is air quality. AVs are anticipated to be EVs as well, as the energy efficiency improvements afforded by of these powertrains would offer a cost advantage, in addition to lower operational and maintenance costs [4]. Additionally, if deployed in shared-use fleets, electric-AVs can negate the range and recharging time issues of conventional EVs, as the SAEV fleet could be centrally managed to be either charged or allocated depending on travel demand [5]. Such opportunities are becoming bolstered with the support of informed policy. In California, Senate Bill 59 (currently under legislative review) would convene a task force to ensure that the deployment of AVs supports the environmental and equity goals of the state, putting pressure on the deployment of vehicles to be concurrently zero-emissions, autonomous, and shared [6]. With technical and policy pressures guiding the deployment of SAEVs, the increasing interactions between the energy grid and local environment must be considered in advance.

The concept of SAEVs may sound futuristic, but the transition towards this paradigm may be feel entirely familiar. One's first interaction with the SAEV paradigm may likely take the form of a transportation networking company (TNC) ride (e.g., from Uber or Lyft), only that ride would arrive without a driver. Take the average California household, which usually owns and operates two cars. The cost of owning and operating a vehicle typically fluctuates between $0.55- $0.75 per mile of driving. Presently TNCs such as Uber and Lyft commonly charge between $1.50 and $2.50 per mile, making it more attractive to own and operate one's own vehicle for most people. However, recent cost-based analyses of autonomous mobility services suggest that SAEV costs could fluctuate between $0.15-$1.00 per mile [7]. Additionally, studies such as those from the University of Michigan estimate that the potential impact on private vehicle usage could reduce the two car households to one car households [8]. In the meantime, significant hesitations with regards to using SAEVs remain. Research has found that even if SAEV rides were completely free, about 25% of people still would refuse to ride [9]. Should you, the reader, be in the 75% of folks to accept the novel SAEV ride, you would likely notice plenty of differences, many of which would significantly affect the energy usage of that vehicle.

You silently, smoothly, ride off to your destination. You may even have the option to share your ride with someone who is traveling in the same direction as you. Altogether, vehicle automation, EV powertrains, and potential for shared (i.e., pooled) mobility result in what is known as the Three Revolutions in Transportation [10]. These revolutions may pose opportunities to help meet energy, climate, and pollution goals (e.g., smoother rides leading to increased vehicle efficiency), or new challenges may emerge (e.g., cheaper and more convenient transportation leading to more trips taken, potentially increasing net energy usage). There are likely to be many opportunities and challenges for the future of mobility beyond these brief examples. This work defines these opportunities and challenges starting with the future vehicles themselves both individually and as part of a larger hypothetical SAEV-deployment, measures the projected impacts to the California energy grid, and measures the corresponding grid and transportation-sector GHG and CAP emissions.

1.2 Goals

The goals of this dissertation are to:

1. Create a simulation framework to design and evaluate SAEV prototypes for vehicle-centric energy impacts related to ZEV powertrain, sensor integration strategy, and improved performance (i.e., via V2V and V2I).
2. Measure the spatial distribution of SAEV Stations in California and corresponding fleet-centric performance (e.g., overall VMT, fleet size, infrastructure requirements, etc.)
3. Measure the impact of the proposed SAEV-network on the CA grid, GHG emissions, and CAPs.

1.3 Objectives

The following objectives are required to achieve the goals of this dissertation:

Objective 1. Measure vehicle-centric energy impacts of SAEVs.

Objective 2. Size and site SAEV stations for proposed deployment construct, and measure fleet-centric energy impacts of SAEVs.

Objective 3. Measure SAEV impacts on California energy grid, GHG emissions, and CAPs.

2. Background

This chapter contextualizes this dissertation, and shares relevant research activities which inform the research direction. Topics reflect the objectives that will be achieved, and range from transportation and vehicular technology, to matters concerning the energy grid and air quality.

2.1 Transportation, Energy, and the Environment

Transportation is the movement of people and goods from one location to another. While transportation previously largely relied on human and animal labor, modern means of transportation largely rely on the combustion of fossil energy resources. As of 2018, transportation as a whole accounts approximately 28% of all energy consumed in the United States, and is the second largest consumer of energy overall according to the U.S. Energy Information Administration (US EIA) [11]. As with the other sectors, energy demand is generally increasing over time, as can be seen below in Figure 1.

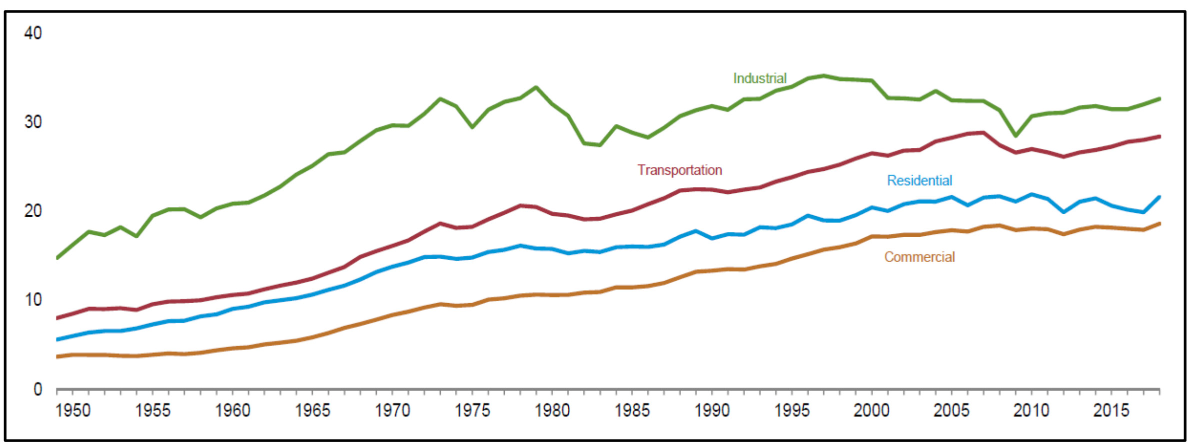

Figure 1: Energy Consumption by Sector, 1949-2018, Quadrillion BTU (Source U.S. EIA)

The primary source of energy for the transportation sector is petroleum, and the associated greenhouse gas (GHG) impact of transportation is larger than any other sector, as shown in Figure 2.

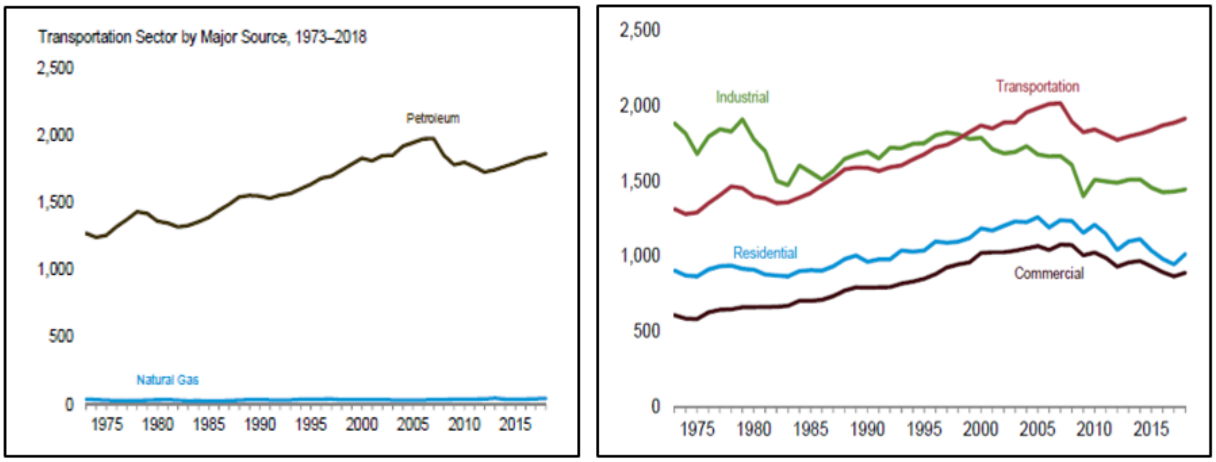

Figure 2: (Left) Transportation Sector Energy Consumption, by Major Source, Quad. BTU (Source U.S. EIA) (Right) Carbon Dioxide Emissions from Energy Consumption by Sector (MMT CO2), Source: (U.S. EIA)

The transportation sector includes air, rail, waterway, and roadway means of travel. Of these modes, transportation via roadway accounts for 82% of domestic GHG emissions [12]. Light-duty vehicles (LDVs) such as passenger cars, vans, and pickup trucks contribute the most towards overall transportation sector GHG emissions at 59%, as seen below in Figure 3.

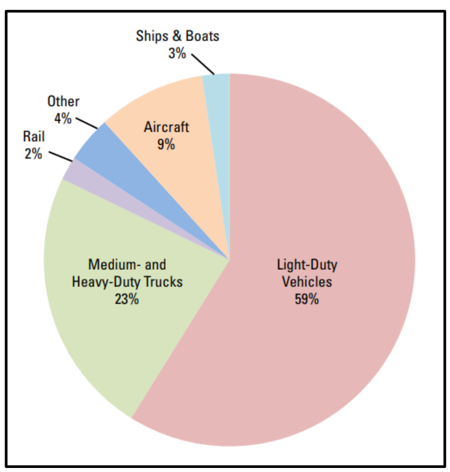

Figure 3: U.S. Transportation Sector GHG Emissions by Source, 2017, Source: U.S. E.P.A.

Note that despite the energy consumption of LDVs increasing as a whole in the US, the efficiency of individual LDVs sold in the US has been trending upwards significantly in the past few decades, as illustrated in Figure 4 [13].

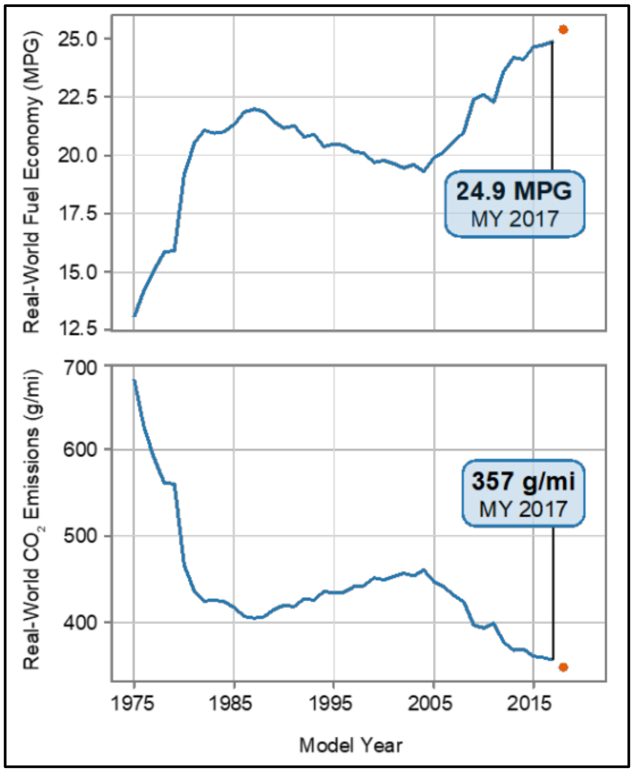

Figure 4: Estimated Real-World Fuel Economy and CO2 Emissions, Source: US EPA

Of the LDVs on US roadways, only a small number are EVs, such as Battery Electric Vehicles (BEVs) and Fuel Cell Electric Vehicles (FCEVs). Though EVs are just a small number of the overall LDVs in the United States, the number of EVs is expected to increase throughout the United States as depicted in Figure 5 [14].

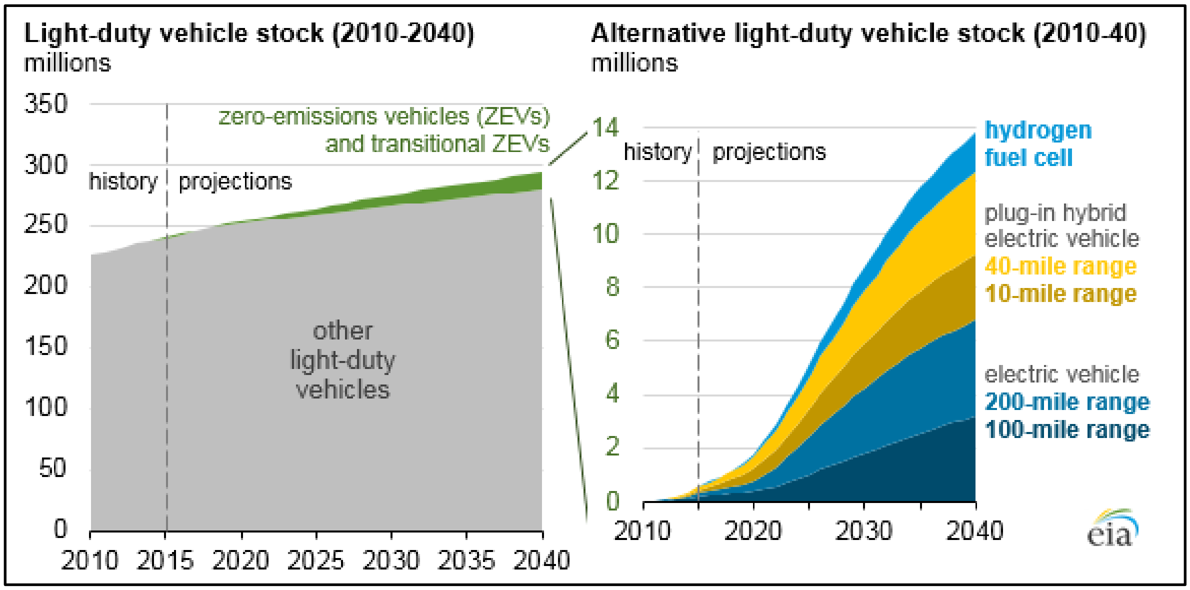

Figure 5: U.S. Light Duty Vehicle Stock, Present and Projected (Source: U.S. EIA)

California is a particularly ambitious state when it comes to the transition towards EVs from ICVs, even though the efficiency of ICVs is increasing. California has approximately 500,000 on the road as of 2019, the most EVs of any state. While this represents about 3.5% of the total 14.8 million LDVs registered in California, former California Governor Edmund G. Brown Jr. issued an Executive Order calling for 5 million EVs to be on California roads by 2030 [15], [16].

The transition towards EVs in California is rooted in the challenges for attaining healthy air quality for much of the state. Figure 6 shows that on a relative scale, counties in California are the most severe areas of non-attainment for National Ambient Air Quality Standards (NAAQS) of the Criteria Pollutants: Lead, Carbon Monoxide, Ozone, Particulate Matter of sub-10 and sub-2.5 micrometers in diameter, Sulfur Dioxide, and Nitrogen Dioxide. Much of central and southern California struggle to meet air quality standards at least six of the seven criteria pollutants.

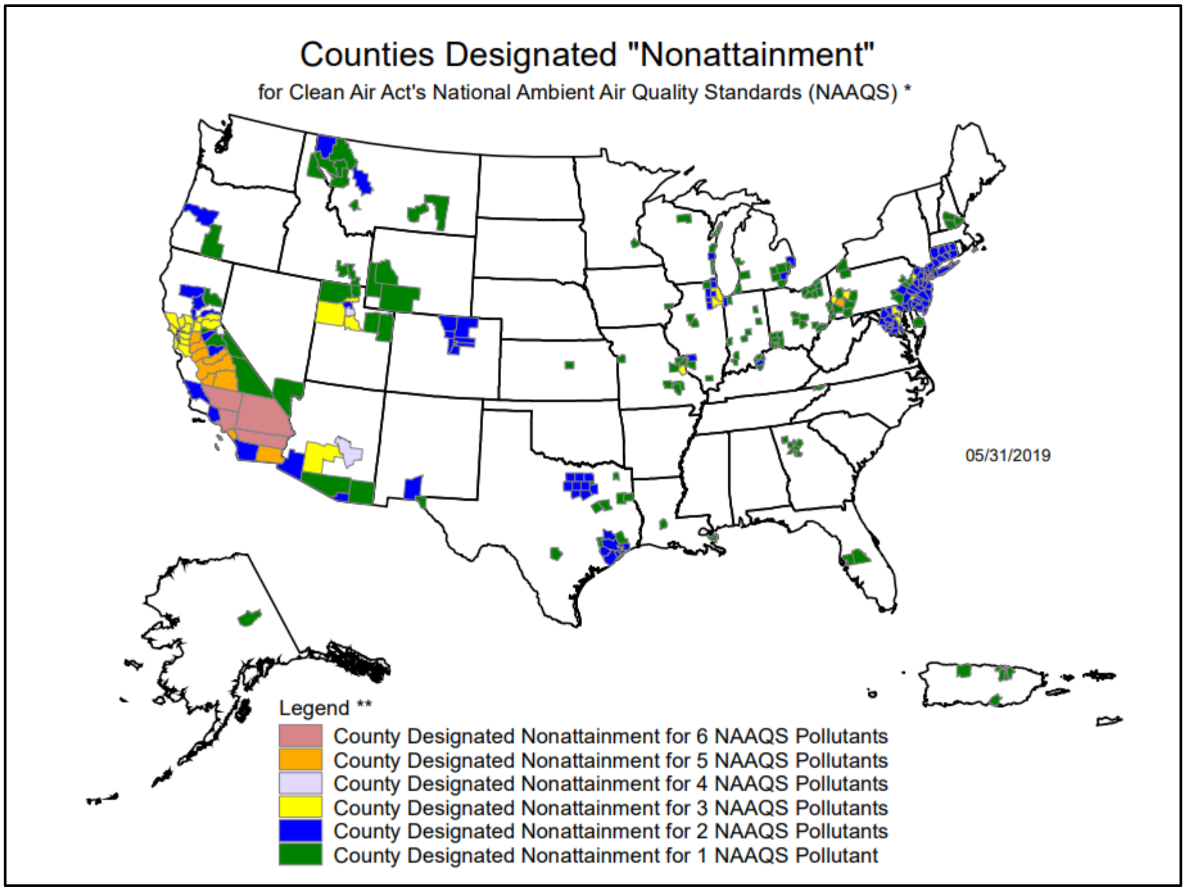

Figure 6: U.S. Counties in Nonattainment of National Ambient Air Quality Standards, 2019, Source US EPA

Such nonattainment in California is predominantly the result of transportation sector activity, though unlike GHG impacts, LDVs overall emit less criteria pollutants than HDVs for California [17]. No matter, such nonattainment clearly remains a pernicious issue for California, and thus necessitates emissions reductions of the LDV fleet via a transition to EVs or by other emerging opportunities in transportation.

2.2 Transportation Revolutions: Autonomous, Electric, and Shared

The conventional automobile that has become ubiquitous over the past 100 years is one that uses human inputs for driving decisions, one that uses petroleum fuel, and one that mostly conveys a single person from place to place. Researchers have identified the convergence of several automotive trends: that vehicle automation is becoming a reality, electric powertrain technologies (i.e., those of BEVs and FCEVs) are becoming more accessible, and the public is increasingly in favor of shared on-demand mobility options (e.g., ride hailing and ridesharing) [10]. This dissertation aims to quantify what these revolutions together can portend for the energy grid and environmental quality in California. Therefore, a brief background on each is provided.

2.2.1 Autonomous Vehicle Overview

Until recently, the notion of a car driving itself was considered a little more than science fiction. This all but confirmed with the DARPA Grand Challenge of 2004. Teams consisting of the best robotics engineers and researchers from around the world assembled upon a 130-mile-long stretch of American desert roadway to test their self-driving vehicles. The first robot to complete this course would win, so long as the only human input was a command to start the journey. Unfortunately, none of 100-or-so teams made it farther than seven miles. Some took this conclusion as proof of conventional wisdom – that robotic cars are still a long way off, and that so called smart-vehicles would require smart-roadways (i.e., supporting infrastructure to help the vehicles along).

But the 2005 re-match saw several teams completing the challenge. These teams proved that it is possible for robotic vehicles to traverse roadways without help from the roadways via embedded magnets, wires, or the like. This meant that the deployment of autonomous vehicles may not necessarily depend on local government investment into infrastructure. Rather, autonomous vehicles were proven capable of assessing their surroundings with built-in sensors and reaching safe driving decisions on their own. Recognizing this opportunity, Google hired former participants in the DARPA Challenge, and in 2010 unveiled their Google Autonomous Vehicle Project, now named Waymo. The rate of progress was shared to be 5-years of safe driving in 2010, 1000 in 2012, and (from a fleet of 24 vehicles) 50,000 in 2014. Now, as of 2019, a human is required to take control of a Waymo autonomous vehicle about once every 11,000 miles on public roads [18]. This is essentially the same distance the average American drives each year, all while needing to take control of the vehicle one time [19]. From an odds-defying 130-mile journey in remote desert, to an average of 11,000 miles of safe driving in dynamic, everyday streets in the span of about 15 years. There is good reason why autonomous vehicles are taken seriously as a potential solution for some of the most serious problems of contemporary life.

State-of-the-art autonomous vehicles depend on a suite of sensor technologies to perceive the surrounding environment and make safe driving decisions. Many sensors are already being installed on contemporary human-driven vehicles to enhance safety and have the potential to enhance fuel economy [20]. The sensors typically installed include some combination of the following: Vehicular Camera Systems (VCS), Vehicular RADAR Systems (VRS), Vehicular Ultrasonic Sensors (VUS), LiDAR, Vehicle to Vehicle Communications Systems (V2V), and Vehicle to Infrastructure Communication Systems (V2I). Each sensor offers a different perspective on the surrounding environment, and each has strengths and weaknesses. Therefore, it is common practice to combine sensors for comprehensive and robust perception.

Contemporary autonomous vehicles fall into two general categories for sensor installations, low-profile and high-profile as illustrated in Figure 7 below [21], [22].

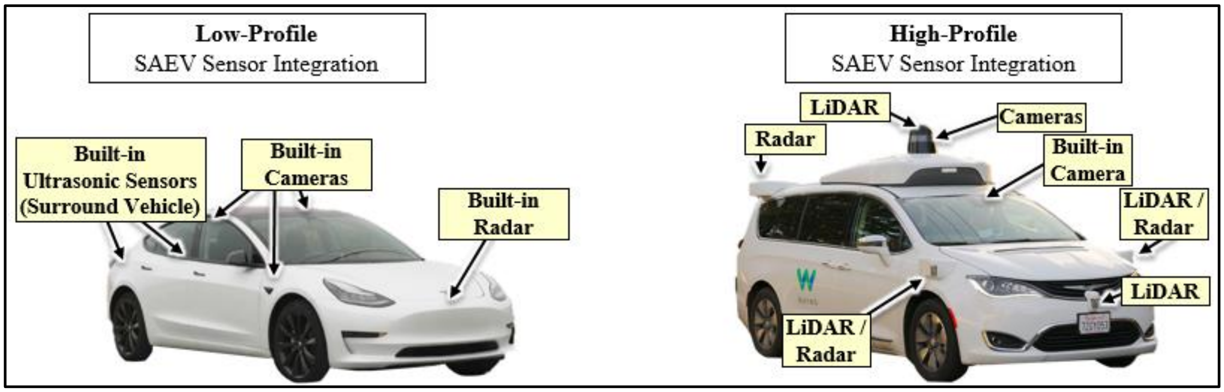

Figure 7: Low and High-Profile Autonomous Vehicle Sensor Integration

A brief overview of common autonomous vehicle sensors is provided below.

2.2.1.1. Vehicular Camera Systems

A VCS measures and processes visual information via one or more cameras together with image processing software. VCSs are relatively lower cost than other sensors and are typically simpler and easier to install [23]. However, the effectiveness of a VCS depends on the quality of visual information near the sensor and vehicle. Such visual quality can be dramatically affected by poor weather conditions or by dust and debris [24].

Contemporary uses for VCSs are in safety features, such as detecting unsafe vehicle distances in Forward Collision Warning systems and unsafe lane position in Lane Departure Warning systems [25]. It is likely that VCSs will become more useful as innovation in continues in image processing, and computing power continues to decrease in cost [26]. While safety improvements are already being realized, modern VCSs are beginning to reliably distinguish between roadway objects such as pedestrians, cyclists, trucks, cars, and traffic signs in complex real-world driving scenarios [27].

2.2.1.2. Vehicular Radar Systems

A VRS measures the position and movement of an object by emitting and detecting radio waves as they reflect off objects surrounding the vehicle with typical ranges between 100 and 200 meters [28]. Much like VCSs, VRSs have been proven effective in the safety context, and they have been merged with VCSs for use in Forward Collision Warning systems and Adaptive Cruise Control systems. VRSs are limited in their ability to interpret details of the object they are detecting (e.g., a VRS cannot decipher the information on a sign as a VCS may be able to), but VRSs can provide robust object detection measurements despite visual obscurities, making for a strong pairing between a VRS and VCS [29].

2.2.1.3. LiDAR Systems

LiDAR operate similar to VRSs in principle, only that LiDAR sensors emit and detect the reflection of infrared light from surrounding objects for environmental perception [30]. LiDAR sensors, which are currently exclusively used for autonomous vehicles, typically send precise beams of infrared laser light in 3-dimensions, creating a perception of nearby objects that does not depend on available ambient light, like a VRS, and is able to distinguish between object type (e.g., pedestrian or vehicle, etc.), like a VCS [31]. However, also similar to a VCS, LiDAR effectiveness can be compromised by visual obscurities such as precipitation and debris. While presently LiDAR is included in numerous contemporary autonomous vehicle designs, the future importance of LiDAR in autonomous vehicles is less certain. As VCS image recognition and computational techniques improve, LiDAR may offer relatively less advantages, and may continue to be a relatively technologically complex and expensive sensor compared to VCSs [32].

2.2.1.4. Ultrasonic Sensor Systems

Ultrasonic sensors operate like VRS in concept, though ultrasonic sensors emit and detect high frequency sound waves to gauge distance. These sensors are similar to VRS in that they do not depend on visual information for measurements, and are similar to VCSs in particular due to relatively low cost, technological simplicity, and that they are increasingly common in modern vehicles [33]. However, unlike VRS, they are used for proximity warnings, typically within several meters, such as blind spot monitoring on highways or in parking accident prevention. For use in an autonomous vehicle, ultrasonic sensors are a relatively inexpensive means of adding robustness to visually garnered information through VCSs.

2.2.1.5. Vehicle to Vehicle Communication (V2V) Systems

V2V systems exchange telemetric data between two or more vehicles. Such data may include: time, location, vehicle ID, velocity, acceleration, braking status, and more. V2V systems typically operate using Dedicated Short-Range Communication (DRSC), which uses Wi-Fi transmitters with range of approximately 300 meters, as defined in the Wireless Access in Vehicular Environments (WAVE) standard [34]. V2V has safety applications just like VRSs and VCSs, while also having relatively high potential energy savings [35]. V2V allows for coordination between vehicles not necessarily in the direct vicinity, or in the line-of-sight of the vehicle. For example, platooning is a V2V-supported energy saving concept where two or more vehicles can safely follow one another at close distance as enabled by the coordination of vehicle speeds. The result of this closer following distance is decrease in aerodynamic drag, and thus, a reducing in the force and energy required for the following vehicles [36]. As another example, perceiving the locations, speeds, accelerations, and decelerations of surrounding vehicles allows the V2V-enabled vehicle to perform driving actions in a more efficient manner than otherwise possible. A V2V-based efficiency-promoting driving suggestion tool was created to measure the impact of such smoother driving behavior, which increased fuel economy by approximately 20% for otherwise aggressive drivers, and about 5-10% for more moderate drivers [37]. Researchers have also found that it isn't necessary to have roadways entirely populated with V2V-enabled vehicles to garner benefits. Studies using computer simulation have shown that safety and efficiency benefits are possible to achieve with only about 5-10% of vehicles connected (i.e., V2V-enabled), with valuable traffic density information possible to garner with as little as 2% of a vehicles connected [38]–[40].

2.2.1.6. Vehicle to Infrastructure Communication (V2I) Systems

Just like V2V systems, V2I systems exchange telemetric data to perceive the environment. A V2I system is essentially a V2V system, only used not to communicate information between vehicles but between vehicles and one or more infrastructure points on roadways or traffic lights. V2I and V2V systems predominantly use the same basic wireless technology to enable data transfer. To help differentiate between these two systems, some applications of V2V technology may include: platooning and cooperative adaptive cruise control (CACC), pre-collision and lane-change warnings, and for emergency messages alerting traffic of a disabled vehicle ahead. Depending on the exchange of information between vehicles and the infrastructure, some applications of V2I technology may include some of the aforementioned V2V applications, though more common V2I applications enable the cooperation between vehicles and traffic signals such as Signal Phase and Timing (SPaT), and Variable Speed Limit controls [41], [42]. As with V2V, vehicle efficiency can be enhanced by cooperation between vehicles and infrastructure by reducing stop and go traffic and other often preventable speed oscillations. V2I technology has been found to have a potential fuel economy benefit somewhere between 10-25%

in real-world demonstration projects, and up to 40% in situations where stop-and-go behavior at traffic lights is prevented in computer simulations [43], [44].

2.2.2 Electric Vehicle Overview

Whether motivated by environmental concerns, energy security, or by improved performance, the future of transportation is shifting from petroleum dependent ICVs and towards BEVs and FCEVs. Both EVs have no harmful tailpipe emissions, and both represent a major improvement from the negative consequences of our current ICV paradigm. But in the context of an autonomous and shared future, one must explore the numerous tradeoffs between these different technological platforms.

2.2.2.1 Battery Electric Vehicles

Battery Electric Vehicles (BEVs) have been increasing in number on domestic roads at a slow but steady pace, but they are nothing new. BEVs were invented in 1834, and BEV taxi fleets were operating in London in the late 19^{th} century [45]. Despite early success, BEVs quickly fell out of favor when the better range and refueling time of the ICV platform came into prominence in the early 20^{th} century. The ICV has dominated LDV mobility worldwide ever since, and only recent environmental motivations together with technological improvement (e.g., larger range and shorter recharging time) have brought BEVs into focus as a favorable LDV mobility option.

BEVs use chemical potential energy stored in batteries to provide electricity for electric motors, which use this electricity to propel the vehicle forward. While numerous battery choices for use in BEVs are available, the choice in battery technology will dictate vehicle range, power, charging rate, weight, and operating conditions such as suitable temperatures. Previous BEVs have used Lead-Acid Batteries (LABs), such as the early versions of the General Motors EV1 from the mid-1990s. However, low energy and power density made for relatively heavy vehicles that could not compete favorably with ICVs, and the use of lead raises environmental concerns [46], [47]. As with other BEVs of the late 20th century, the second generation EV1 was outfitted with Nickel Metal Hydride (NiMH) batteries. NiMH batteries improved the performance slightly from LABs and lessened the environmental concerns of the previous batteries, but ICV performance in terms of range and speed of refueling was still significantly better from the user perspective. Contemporary BEVs which rival ICVs use Lithium-Ion (Li-Ion) Batteries, which have greatly improved the performance of automotive battery packs. Typical Li-Ion BEVs, such as the Tesla Model S, provides range of up to 300 miles with the ability to charge to 80% battery capacity in as little as 40 minutes. While the expense of BEVs with such performance is greater than comparable ICVs, researchers believe that costs will decrease to the level of mass-market consumer appeal sometime in the 2020's [10].

BEVs are an EV option that is supported by an electricity grid. BEVs can be charged at different rates, referred to as one of three levels, as shown in Table 1 below:

Table 1: BEV Charging Levels, Power Options, and Notes

Charging Level	**Power (V*A=kW)**	**Notes**
Level 1	120V * 20A = 1.4kW	Level 1 is the standard wall-outlet power rating for the United States. With as little as a 5-miles-of-range per hour, this level could take to 52 hours to fully charge a 300-mile BEV
Level 2	208V * 40A = 6.2kW Or 240V * 40A = 7.6kW	Level 2 is also a commonly found household power rating, usually for large appliances such as clothes driers. When charging vehicles, BEV owners can expect about 22-miles-of-range per hour, which could take about 12 hours to fully charge a 300-mile BEV.
Level 3	600V * 400A = 240kW	The fastest option available, Level 3 can charge at the rate of 300-miles-of-range per hour.

The environmental impact of BEVs largely depends on the mix of energy resources that supply that energy grid, as the environmental detriment of the mining, transport, production, and disposal of BEV batteries has been found to be relatively insignificant by comparison [48]. While ideally the electricity used in BEVs would be renewable and clean, the domestic energy resources in the United States are all sufficiently efficient to provide BEVs with clean enough power to represent a significant environmental improvement from ICVs [49].

In the context of autonomous and shared vehicles, BEV-SAVs don’t need to charge when convenient for the consumer (e.g., BEV owners tend to charge their vehicle right after work) and can charge based on the demand for SAEV trips. Assuming most commuters continue to travel in morning and evening peaks, a fleet of BEV-SAVs could charge at times and rates more directly amenable to production and use of energy resources. This could mean charging BEV-SAVs at level 3 during peak solar energy production, which corresponds to a lull between peaks of travel, or charging at level 1 or 2 in the nighttime for load-balancing purposes.

2.2.2.2 Fuel Cell Electric Vehicles

Fuel Cell Electric Vehicles (FCEVs) use the chemical potential energy between Hydrogen and the Oxygen in air to create electricity using a fuel cell, which electricity is then used in electric motors to provide motive force. Compared to BEVs, FCEVs typically offer higher range at a lower price point, and as of 2018, a 300 mile FCEVs tends to cost about half that of a comparable BEV [10]. This is because FCEVs take advantage of the relatively high energy density of compressed Hydrogen gas, which allows not only allows the FCEV a relatively high range but also a faster refueling time, which is on the order of 5 minutes relative to the 40 minutes for a BEV. As of 2018, approximately 5,000 FCEVs are registered in California, and supported by about 40 hydrogen fueling stations with about 20 more with funding secured to come [50].

As with the environmental impact of sources of electricity for BEVs, one must consider the environmental impact of the sources of hydrogen gas used for FCEVs. As of 2019, 95% of all hydrogen gas domestically produced comes from the steam methane reformation (SMR) of fossil-derived natural gas [51]. Even if using this fossil fuel, when used in FCEVs, the total carbon emissions of an FCEV using SMR-produced hydrogen is half that of a conventional ICV [52]. Just as the electricity grid can get cleaner with more renewable resources, so can the national hydrogen supply. For example, SMR can create hydrogen from bio-renewable methane sources such as wastewater treatment plants or landfills. Hydrogen can also be created by splitting water molecules apart in a process called electrolysis. The electricity used for such process could be renewable sources such as solar and wind, or low carbon such as hydropower or nuclear power. The concept of using renewable energy to electrolyze water for FCEVs has already been explored in depth by the academic community and industry alike [53], [54]. Recognizing these opportunities to further reduce the overall carbon intensity of FCEVs, California has set the goal of dispensing hydrogen with at least 34% renewably-derived hydrogen at all in-state stations by 2024 [55].

In the context of autonomous and shared mobility, FCEVs offer the strength of long range, fast refueling times, and less dependence on the surrounding electrical infrastructure. Researchers have found that the downtime caused by short range and long refueling time necessitates a larger SAV fleet to accommodate travel demand [5], [56], [57]. Therefore, the range and fueling performance of FCEVs could make for an attractive SAV powertrain option.

2.2.3 Shared Mobility Overview

The concept of people sharing cars, bikes and scooters is nothing new. But recent innovations of GPS-enabled internet-connected devices and social networking platforms have made sharing modes of transportation easier and more convenient than ever before [58]. The term Shared Mobility is broad but is accepted to include services such as: ride-hailing (e.g., such as Uber and Lyft), ride-sharing or carpooling (e.g., UberPool, Waze Carpool), crowdsourced private shuttles (e.g., Bridj), and short-term mobility rentals (e.g., Zipcar and Car2Go for automobiles, JUMP for bikes and scooters). Transportation Networking Companies (TNCs) such as Uber and Lyft have recently evolved to become shared mobility platforms, allowing the consumer to choose the mode of transit they would like at that moment, whether a ride in a private car, a shared ride in a carpool, or a quick trip on a bicycle or scooter – all from one smartphone application.

The increasing prominence of this technology-enabled Shared Mobility presents an opportunity to dramatically reduce transportation costs and improve transportation efficiency, particularly through easier and more convenient access to carpooling (i.e., enabling more people to share a single vehicle). Researchers note that automobiles are among the most underused capitol assets in the U.S. economy, being that they sit unused approximately 95% of the time, only to convey one occupant and therefore just a fraction of the capacity, the remaining 5% of the time [10]. Given the millions of vehicles around the world, recent Shared Mobility products offer a chance for consumers to not only benefit from potential cost savings, but also from a reduction in energy consumption and associated environmental consequences. These are recent shifts pushed by consumer demand, and it’s not just TNCs embracing this potential. Nearly all major automakers are at least discussing the consumer shift in preference from a private-ownership model to more of a shared-ownership model, with some automakers investing in

TNCs (e.g., Daimler in Uber and Car2Go, GM in Uber and Lyft, Toyota in Uber, Ford in Lyft, etc.).

If the trips of the future occur in autonomous and electric vehicles, with only one person per vehicle as is common today, just a fraction of the potential benefits would be realized. One benefit of shared (i.e., “pooled”, in this context) mobility would be a decrease in the number of vehicles necessary to support passenger travel. Researchers from MIT used a public dataset consisting of about 3 million taxi rides from over 13,000 New York City taxis to explore the potential for shared vehicles to accomplish these trips instead of, mostly, single customer rides. Shared vehicles with capacity of 1, 2, 4, and 10-seats were allocated between customers in a computer simulation using these real data, and performance was measured in terms such as waiting time and percentage of trips served. The researchers found that when efficiently shared, fleets of 3,000 vehicles a with 2 and 4-seats could serve 94% and 98% of requested trips with only 3.2- and 2.7-minute wait times, respectively. A fleet of shared 10-seat vehicles with a 2.8-minute wait time would need to consist of just 2,000 vehicles, approximately 14.7% of the current NYC taxi fleet [59].

2.3 Autonomous Vehicle Energy Impacts Overview

Transportation is becoming increasingly autonomous, electric, and shared. Researchers anticipate these shifts to have tremendous energy implications, which could be either positive or negative. A recent effort between several U.S. national laboratories quantified what these positive and negative energy impacts could be, and concluded that overall LDV energy use could either decrease by 60%, or increase by 200% [60]. Considering the environmental consequences and matters of energy security at stake, one must explore what affects these changes in transportation energy usage in greater detail. For the purposes of this work, the following two categories of energy impacts will be explored:

1) Vehicle-centric energy impacts, as related to energy efficiency possible on individual SAEVs

2) Fleet-centric energy impacts, as related to how fleets of SAEVs are allocated and used.

2.3.1 Vehicle-Centric Energy Impacts

Vehicle-centric SAEV energy impacts are generally positive. Aside from some additional weight, power consumption, and aerodynamic drag of SAEV sensors and computers, a significant overall benefit remains for deploying these sensors on the vehicle, as they enable individual SAEVs to drive more smoothly and efficiently (i.e., perform eco-driving). Moreover, if a consumer opts for a single-passenger ride, a one-seat vehicle may be allocated to that individual. The corresponding energy savings comes from the replacement of a 4-seat sedan most conventionally commuted in today with a smaller, lighter, and more energy efficient vehicle. When smoother-driving behavior is used to pilot more energy efficient vehicles, the result is compounding. U.S. national laboratories have found that eco-driving and vehicle resizing could reduce the energy consumption of SAVs by approximately 15% and 35% respectively, relative to a conventionally driven vehicle, as shown in Figure 8 [60]. When summed, the total vehicle-centric SAV energy impact can be expressed as the upper and lower bounds, as influenced by how much or little specific SAV characteristics affect the total energy consumption of that vehicle. These bounds are estimated to be between a maximum of 60% energy savings when compared to conventional vehicles to a minimum of 5% energy savings.

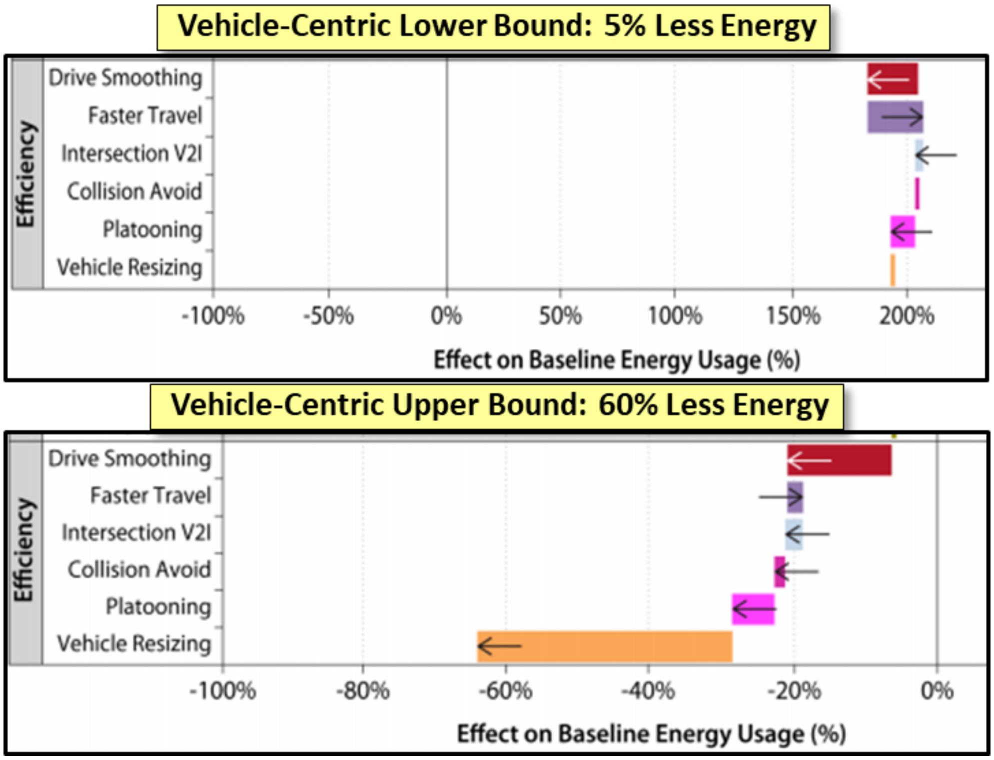

Figure 8: Vehicle-Centric SAV Energy Savings Estimation Bounds (Source: US NREL)

From this work, one can conclude that the largest potential for vehicle-centric energy savings comes from eco-driving (referred to as "Drive Smoothing" above) and vehicle re-sizing, relative to the other potential changes from SAEV technology. Smoother driving behavior can largely be affected by the vehicle technologies mentioned in section 2.2.1 Autonomous Vehicle Overview. For example, sensor combinations such as VCS and VRS can detect upcoming traffic situations and can help prevent fuel from being wasted by approximately 15% [61]. Connected vehicle technologies such as V2V and V2I can also play a significant role in eco-driving, as V2I can allow for coordination between stoplights and upcoming vehicles to prevent unnecessary stops, and as V2V can prevent stop-and-go traffic and enable platooning. These, and implications of vehicle re-sizing, will be addressed in greater detail in Chapter 4.

2.3.2 Fleet-Centric Energy Impacts

Fleet-centric energy impacts pertain to the overall usage of SAEV fleets. SAEVs are expected to bring forth an even more convenient, accessible, and affordable transportation paradigm than what currently exists. This is a good thing in the sense that many underserved peoples (e.g., those with physical or financial limitations) will be able to benefit from greater access to transportation. However, the mindful allocation of SAEVs will be necessary.

Historical transportation trends warn of negative consequences on the horizon. Historically, when transportation become more affordable and convenient, people will travel farther distances. This has been the case from walking, to horseback, to the present-day usage of the privately-owned automobile. Researchers have provided a glimpse at what SAEVs could portend here by giving people access to SAEV-like services via free on-demand chauffeured vehicles. The result of this SAEV-like mobility service was an average increase in VMT of 83 percent across test-groups of millennials, families, and retirees [62].

Researchers have defined specific factors which can contribute to this VMT increase just as they have with vehicle-centric energy impacts. Their work indicates that fleet-centric impacts are heavily affected by easier travel as mentioned, while also being affected by the new access provided to underserved communities. Estimated bounds are shown below in Figure 9.

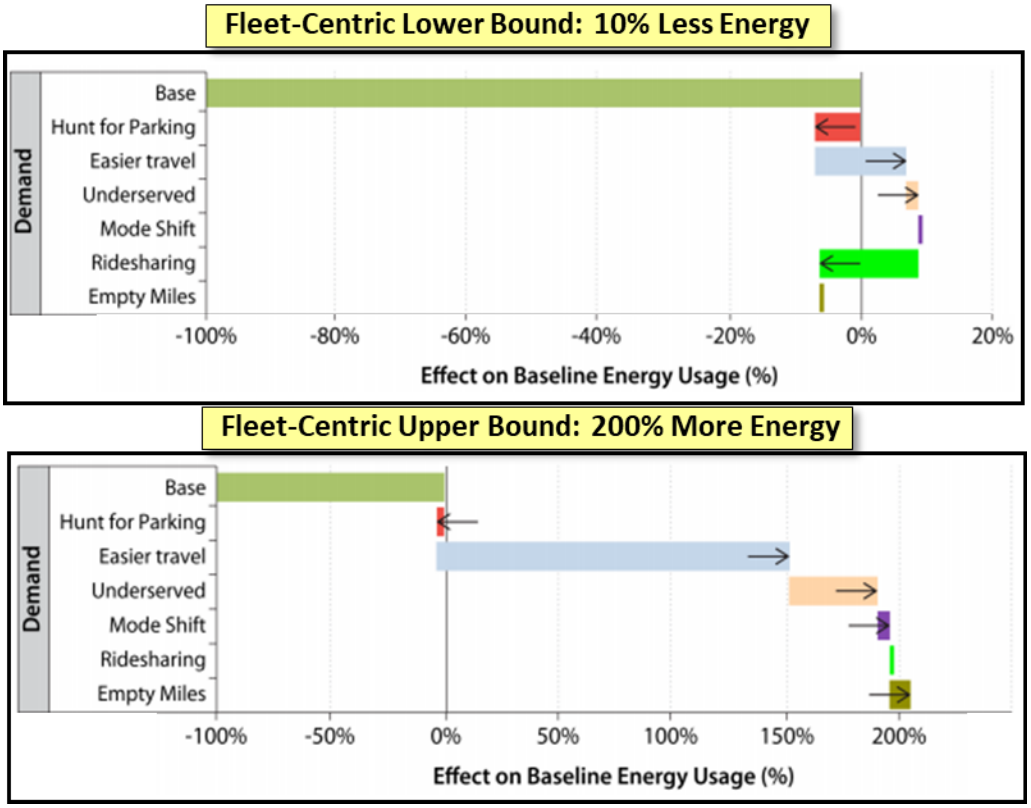

Figure 9: Fleet-Centric SAV Energy Savings Estimation Bounds (Source: US NREL)

From this work, easier travel combined with access for the previously underserved represent the greatest possible increases in energy usage on a fleet basis. This study also quantifies the impact of shared rides in the minimum fleet-centric energy impact scenario. Note the relative effect that ease of transportation has on energy consumption even in the most conservative scenario. Ease of transportation brought on by SAEVs is expected to be a strong factor for future transportation energy consumption. However, the extent to which SAEVs deploy as shared (i.e., pooled) resources will play a significant role in determining how much the fleet-centric energy impacts will cause detriment to the energy and environmental goals set for the transportation sector.

2.3.3 SAEV Stations and SAEV-Deployment Construct

Critical to fleet-centric SAV impacts are the facilities (i.e., stations) that must support such fleets. SAEVs would likely be centrally recharged or refueled, reducing the need for EV-supporting infrastructure in homes, at workplaces, or in various public centers. There are numerous factors to consider for the operation of these stations, with two important factors being station sizing (i.e., number of parking spaces and recharging / refueling spaces) and siting (i.e., physical location). Researchers have investigated numerous deployment strategies, with various sizing and siting parameters, and their impacts to transportation network performance [63]. The construct explored by this work would use parking lots and parking structures, presently common locations for dormant privately-owned vehicles, for the support of SAEVs when in need of fuel or a charge. Therefore, these stations must be able to support the dispensing of alternative fuels, which can be sourced from either renewable or fossil sources. Below is an illustration of a relatively large station concept.

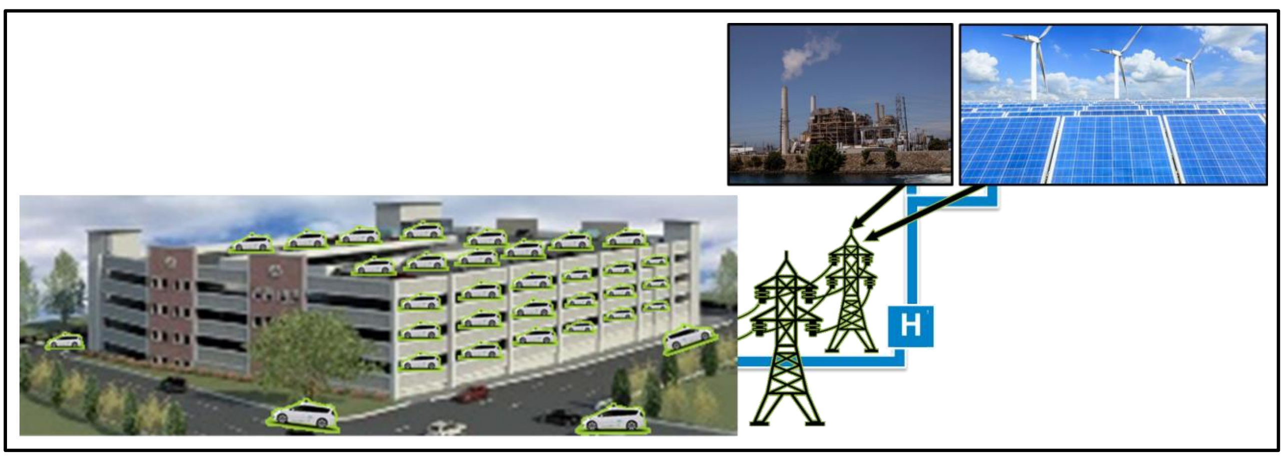

Figure 10: SAEV Station Concept

Groups of such SAEVs stations, sited to efficiently serve nearby neighborhoods, form the basis for the SAEV deployment construct mentioned in the title of this dissertation. Specifically, the SAEV deployment construct for this work (i.e., the hypothetical “Nice-SAEV” program) refers to the management of prototype SAEV fleets as they travel to-and-from SAEV stations and within nearby neighborhoods. The imagined purpose of the hypothetical Nice-SAEV program is to replace short-distance conventionally-driven trips throughout California with safe and efficient SAEVs. The research purpose for the Nice-SAEV program for this work is to provide a consistent framework (i.e., construct) for which to compare various prototype SAEV designs and measure the resulting fleet-centric impacts. Fleet-centric impacts are measured per prototype SAEV-design and include: total number of vehicles required per fleet, number of VMT, number of parking spaces required per SAEV station, number of charging/fueling-spaces required per station, and total energy consumed per day. Specific operating parameters are described in greater detail in Chapter 5.1, The “Nice-SAEV” Car and Ridesharing Program.

There are many potential strategies for operating such a SAEV station construct. Generally, a shrewd SAEV fleet management strategy would likely operate vehicles to either be 1) conveying people or goods for revenue, 2) getting charged, refueled, or fixed, or 3) providing the energy grid with strategic load and ancillary services (e.g., vehicle-to-grid interaction, or V2G). The SAEV station is therefore a place of great activity. While possible with privately owned vehicles, user skepticism of providing grid services (e.g., more wear on the expensive-to-replace battery) and resistance to behavioral change (e.g., not wanting to drive on empty to work to charge) have proven to be significant in early grid-service-focused demonstrations. A SAEV fleet could ultimately transcend this concern and potentially allow for cooperation between the needs of the local power utility and the SAEV fleet via V2G or other grid services.

Note that the scope of this dissertation covers BEV and FCEV-powertrain SAEVs, with BEV SAEVs operating with two different immediate charging protocols. Just as there are numerous possible prototype vehicle designs and this work opts to choose several to create and evaluate, there are numerous possible charging and fueling protocols, amongst many other SAEV-construct design decisions, from which a select few were chosen to form a basis for comparison. The purpose of this work is not to definitively predict the performance of future transportation networks, but rather contribute a toolset (e.g., FETCH) and research method (e.g., employing FETCH with ArcGIS, CSTDM, a SAEV-fleet management strategy, HiGRID, and GREET, etc.) for continuously evaluating the potential impacts of upcoming SAEV deployments.

2.4 Energy Grid Overview

The energy grid is the network that produces and distributes energy resources (e.g., electricity, petroleum, natural gas, hydrogen, etc.) for consumption. The energy grid pertinent to this work is the California grid of electricity and hydrogen.

2.4.1 California Electricity Grid

Electricity grids generally follow the same architecture of production and distribution throughout the world. This architecture is illustrated below [64]:

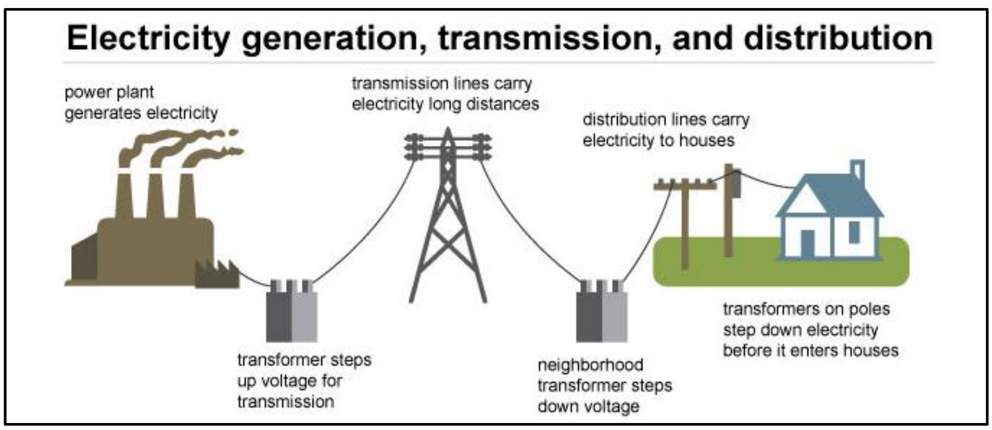

Figure 11: Basic Electricity Grid Architecture

Note that the power plant in the left of Figure 11 is flexible and can include many electricity producing resources, not necessarily ones that produce pollution as they generate electricity. As of 2018, California's electricity grid consists mostly of fossil resources, by installed capacity, as shown in Figure 12 below [65].

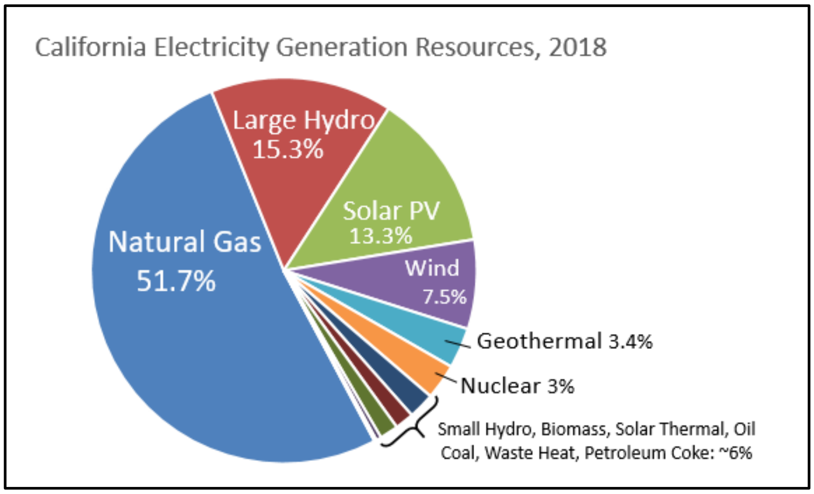

Figure 12: California Electricity Generation Resources, Installed Capacity, 2018, Dara Source, California Energy Commission

As one can see, just over 50% of the generation capacity of the present California electricity grid uses fossil fuels. This dependence on fossil resources in California is continuously decreasing in favor of renewable sources of electricity. Former California Governor Edmund G. Brown Jr. signed *Senate Bill 100: California Renewables Portfolio Standard Program* into law in late 2018, which legally requires 100% of electricity sold to customers in California be from renewable energy resources [66].

The benefits of shifting an electricity grid towards renewable energy resources include a reduction of GHG emissions, reduction of criteria pollutants, and improved domestic energy security. However, the intermittency of renewable energy resources, such as wind and solar photovoltaic (PV), constitute a major challenge for supporting an electricity grid [67]. Intermittency could be the interruption of electricity generation via clouds blocking sunlight or wind speeds changing over the course of minutes, days or weeks. Energy storage technologies such as batteries and pumped hydropower (i.e., using electric water pumps to store water at a higher location, and then allowing water to flow down through those pumps as electrical generators when power is needed) alleviate these issues by providing electricity when needed. For a potential future with vast numbers of BEVs in use, there could be the potential to use the on-board batteries strategically in support of the electricity grid [68]. The need for such creative energy storage solutions is evident in the present-day operation of the California electric grid. Consider Figure 1Figure 13 below, which shows the phenomenon known as the duck curve [69].

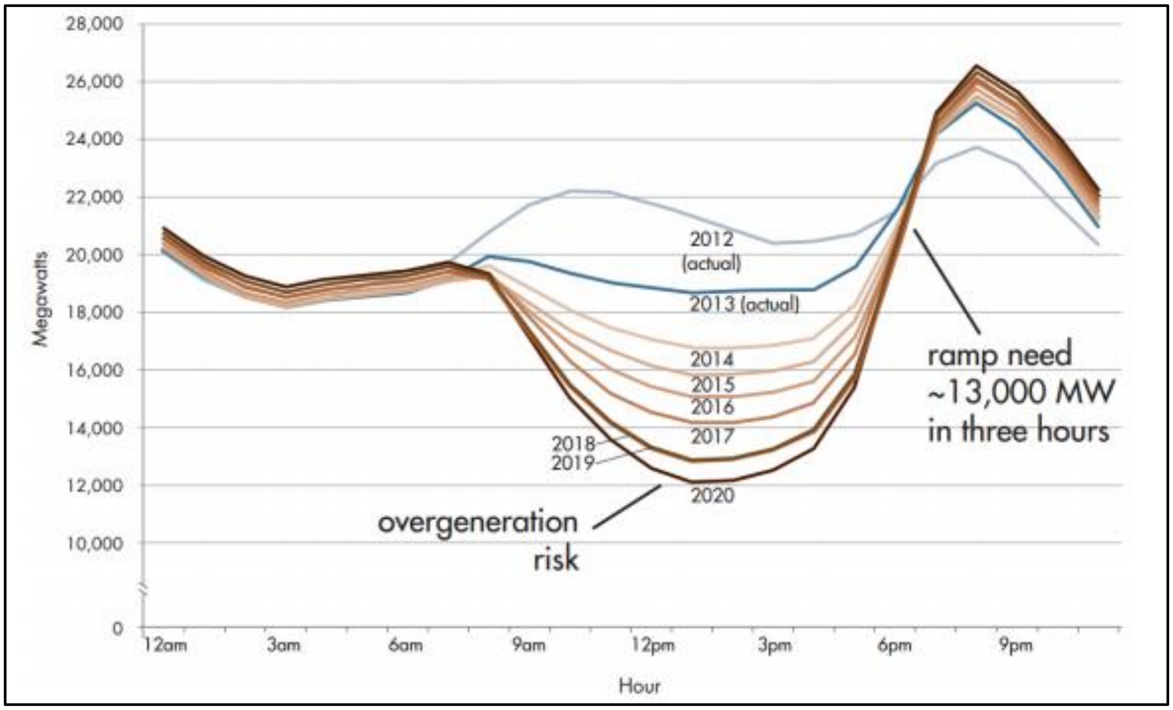

Figure 13: Duck Curve Chart, Actual 2013 Spring Day and Predicted Future Load Profiles, Source: NREL

This figure shows the conventional (i.e., all electricity generated to minus renewable electricity generated) required to support California for a given spring day. As the percent of renewable generation increases, of the reliance on conventional dispatchable electricity generation will be reduced, especially in the middle of the day when solar PV produces the most electricity. While reducing the reliance on fossil energy resources is a positive change, the duck curve phenomenon illustrates challenges that California faces today. The deeper the duck curve sinks, the greater the strain on conventional electricity generation resources that must ramp-up to meet electricity demand at the end of the day, when solar PV no longer generates electricity. The duck curve phenomenon continues to worsen at present, further highlighting the need for energy storage technologies to alleviate adverse interactions between renewable and conventional electricity generation resources.

2.4.2 California Hydrogen Grid

Hydrogen, like electricity, is transported throughout California and can be created (i.e., converted from other molecules into a pure molecular form) from resources that can either derived from fossil fuels or from renewable resources. As described in 2.2.2.2 Fuel Cell Electric Vehicles, about 95% of hydrogen produced today is reformed from fossil resources. However, the hydrogen fuel used for transportation purposes in fuel cell vehicles will be required to contain at least 34% renewable hydrogen in California. Hydrogen is mostly used for industrial processes, such as the refining of petroleum products. Throughout the United States, billions of cubic feet of Hydrogen are produced each day for such purposes, as shown in Figure 14 [70]. One can imagine that the vast quantities of hydrogen presently reformed for the purposes of petroleum manufacture to support ICVs could instead be used to support FCEVs in a future paradigm.

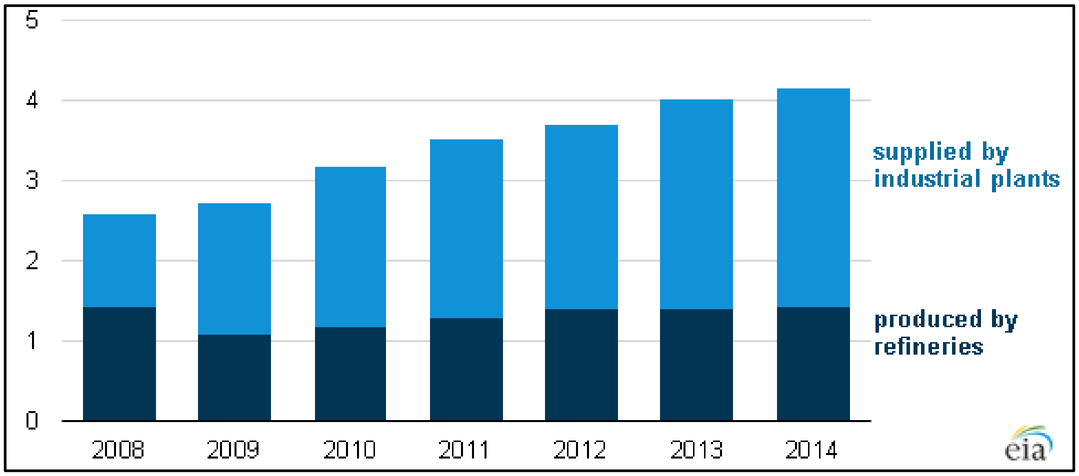

Figure 14: Hydrogen Demand for Domestic Refining Processes (Billions of Cubic Feet / Day), (Source US EIA)

Hydrogen can be produced in large scale (i.e., on the order of 750,000 kg/day) via centralized plants or in intermediate-sized facilities which can produce between 5,000 and 50,000 kg/day of hydrogen [71]. For the purposes of the supporting the futuristic stations described in 2.3.3 SAEV Stations and SAEV-Deployment Construct , one can consider several ways in which hydrogen can be allocated to the FCEV-SAEVs. Firstly, as is the case with supporting conventional hydrogen stations, hydrogen could be reformed at a central location and delivered to the SAEV-station via trucks. Second, the hydrogen could be reformed on-site with an intermediate-sized reformation facility. For perspective on the hydrogen required to support such stations, academic studies have estimated that SAEVs may drive approximately 300 miles per day [72]. Given that FCEVs presently use about 5kg for 300 miles of driving, a fleet of 1,000 FCEV-SAEVs could be require about 5,000 kg of hydrogen per day. This would be possible using an intermediate-sized facility on-site, while eliminating the need for trucking and any associated inefficiencies or emissions, so long as a connection to the (rather extensive) natural gas pipeline would be possible. Furthermore, if renewable methane is used rather than natural gas, the resulting hydrogen would therefore be carbon-neutral overall [73]. On-site hydrogen production can also be achieved with electrolysis. Electrolysis is a technology that is not presently implemented at scale for hydrogen production but represents another possibility for carbon-free hydrogen production by splitting water molecules into hydrogen and oxygen using renewable electricity.

2.4 Background Summary and Research Gaps

This section provides an overview of the relevant research works and research gaps which this work satisfies. There are several areas of interest: 1) vehicle-centric energy impacts of SAEV technologies on prototype vehicles, 2) the sizing and siting of SAEV stations, and 3) the energy grid and environmental impacts of SAEV deployments.

As presented previously, researchers must first measure the energy efficiency impacts of individual SAEVs before measuring their overall energy impact in a larger system. The topic of automotive fuel efficiency is generally rich with research, though historically efforts have mostly concentrated on either improving human-driven ICV fuel efficiency or measuring the energy efficiency of robotic vehicles without consideration of the power, energy, and aerodynamic drag of the installed sensor technologies. For example, in the 1970's domestic studies measured up to 10% fuel economy improvements resulting from human driving behavior as improved with simple instructions and the addition of efficiency gauges for driver reference [74]. Such a study is an early glimpse into what efficiency a more competent robotic system could achieve from the vehicles of that era and driver assistance systems have grown to become increasingly sophisticated. More recently, a joint effort between a number of domestic research labs (i.e., NREL, ANL, ORNL, and the DOE) produced a comprehensive summary and analysis of the various vehicle and fleet-centric energy impacts for ICVs [61] . Gawron et al. estimated the effect of individual SAV-sensors in various configurations of ICV-SAVs and cited how proportionally similar impacts could be expected of BEVs. They ultimately used these estimates for measuring the lifecycle GHG impacts for each configuration, but did not consider the FCEV powertrain [76]. Lee et al. performed an energy impact analysis, though not in the sensor-level detail, and used estimates from past studies to compare overall energy consumption differences between ICVs, HEVs, and BEVs to measure overall vehicle-centric energy impacts [77]. Wadud et al. performed a study to investigate the charges to domestic GHG related to vehicle and fleet-centric aspects and accounted for the difference between ICV and BEV impacts by estimating differences between fuel sources and their impacts [78].

A research gap still exists for a comprehensive SAEV design framework to evaluate the effects of individual SAEV sensors, their potentially negative and positive impact on energy efficiency (due to increased power consumption yet enabling of eco-driving and platooning), all for different SAEV powertrains. Testing SAEVs with BEV and FCEV powertrains, integrating different configurations of SAEV sensors, and testing each with various performance criteria (e.g., V2X range, drag reduction on platooning scenarios, etc.) altogether with the same research methodology, will bridge this gap. The FETCH framework designed to fulfil this requirement and to also remain adequately flexible such that each component of the simulation can be updated as SAEVs begin to take form and technologies improve over time (e.g., higher powertrain efficiency, lower sensor power consumption, etc.).

SAEV-fleets, and the siting and sizing of the stations which support them, has also become a fruitful research topic. Bauer et al. measured the impact of ICV, HEV, and BEV-SAEV fleets for their merit in replacing conventional fleets of New York City taxis. These researchers measured the role of BEV range, charging infrastructure required to support such network, and compared the associated energy consumption, GHG emissions, and criteria pollutants [57].

Chen et al. studied how BEV-SAEVs deployed in Austin, Texas compare with ICV-SAVs on the basis of fleet size and passenger wait time when considering different vehicle range, capacity, and charging rate [72]. Another study in Austin by Loeb et al. explored the role of SAEV fleets on infrastructure siting decisions, finding a strong correlation between BEV-SAEV range and the number of charging stations required [56]. In the broader scale, Brownell et al. performed a statewide study on the fleet size and cost requirements for SAV fleets to perform all LDV trips in New Jersey, though this study did not allocate stations based on passenger demand, nor do they consider vehicle range or wait time [79]. A comprehensive review of such studies was recently published Pernestål et al., in which 26 SAV and SAEV simulation studies are compared in terms of methodologies and findings [63]. They found varying input parameters (e.g., passenger capacity, penetration rate, etc.) yet rather consistent results for waiting times, trip costs, and fleet sizes required. VMT results however, greatly depended on the assumptions made in the preliminary stages of simulation. Of the various vehicle parameters listed, FCEVs were not amongst those technologies compared in any of the studies evaluated.

It is important to note that researchers found advantages to the ICV powertrain relative to BEVs when comparing the required fleet size, largely the result of the greater downtime for due to shorter range and greater downtime to charge. This would suggest that FCEV-SAEVs have a relative advantage (i.e., in terms of the typically higher range and faster refueling time) for supporting a SAEV network with the fewest number of vehicles required.

A research gap therefore exists for a comparison between a BEV-SAEV and FCEV-SAEV network, and a study into the efficient construct and allocation of stations at the state-wide level. As was the case for the vehicle-centric impacts through FETCH, the methods of this research component are also designed such that SAEV deployments can be studied for strategies which may take form in ways not presented in this work (e.g., BEV battery swapping, etc.). Just as with the vehicle-centric impacts, the relevant literature mentioned are used to source reasonable estimations for parameters not directly calculated in this work.

Lastly, interactions between ZEVs, the local energy grid, and the environment have also been rich topics of study. For GHG impacts in California, studies have explored BEV and FCEV fleets of LDVs and HDVs alike for their role in changing the demands on the state-level energy grid [80]–[82]. A similar range of studies have evaluated the environmental impacts of such ZEV fleets in terms of CAP emissions in either specific California air basins or statewide [83]–[85]. This research aims to provide and demonstrate a comprehensive research framework to better define what the environmental impacts of a fleet of BEV and FCEV-SAEVs would be in terms of GHG and CAP emissions, as distinguished from the conventionally-driven BEVs and FCEVs of past studies.

The goals of this dissertation are aligned with the research studies presented thus far. These studies are summarized in the table below for convenient comparison.

Table 2: Relevant Research and Literature Gaps

Authors, year	Journal	Scope	VC: Vehicle Sensors?	VC: Powertrain(s)?	VC: SAV Controls?	VC: Component Energy Impacts?	FC: Vehicle Range?	FC: Compare Vehicle Capacity?	FC: Scope of Study	Grid Impacts?	Environmental Impacts?
Evans, L., 1979 [74]	Human Factors	Assessment of urban driving behavior on fuel economy and trip time using various driver instructions and instantaneous fuel economy readings	No	ICV	No	No	N/A	N/A	N/A	No	No
Tunnell, J., et al. 2018 [86]	SAE	Define the upper limit optimal fuel based on advanced information, measure real-world achievable fuel economy using two ADAS systems	CS	HEV	ADAS	No	N/A	N/A	N/A	No	No
Lee, J., et al., 2019 [77]	[Report. UT Austin]	Estimates overall energy impacts of SAEVs based on summary of relevant energy impact studies	V2V, V2I	ICV, BEV	Eco-Driving, Platoons	Yes (agg.)	N/A	N/A	N/A	No	No
Wadud, Z., et al. 2016 [78]	Transportation Research Part A	Estimates energy impacts due to partial and full automation as defined by various vehicle and fleet-centric estimations, calculates changes in GHG emissions	Agg.	ICV	Eco-Driving, Platoons, Re-Routing, Resizing, Faster Speeds	Yes (agg.)	N/A	N/A	N/A	No	GHG
Stevens, T., 2016 [60]	[Report. ANL, NREL, ORNL, DOE]	Estimates the bounds of overall energy impacts due to various vehicle and fleet-centric impacts and behaviors, in partial and full automation scenarios	Agg.	ICV	Eco-Driving, Platoons	No	N/A	N/A	N/A	No	No

Authors, year	Journal	Scope	VC: Vehicle Sensors?	VC: Powertrain(s)?	VC: SAV Controls?	VC: Component Energy Impacts?	FC: Vehicle Range?	FC: Compare Vehicle Capacity?	FC: Scope of Study	Grid Impacts?	Environmental Impacts?
Gawron, J., et al., 2018 [76]	Environ. Sci. Technol.	Measures energy impact of SAEV sensors, performs life cycle assessment of impact on SAEV and assoc. GHG	Agg.	ICV, BEV	Eco-Driving, Platoons, V2I, Faster Speeds	Yes	N/A	N/A	N/A	No	GHG
Chen, T., et. al. 2016 [72]	Transportation Research Part A	Single occupancy SAEV fleet simulated using agent-based model, measures effect of range and charging rate (L2/L3) on: fleet size, VMT, passenger wait time, estimated trip costs, and vehicle replacement	No	BEV	No	No	Yes: 80, 200 mi.	No: SOV	City: Austin TX., USA	No	No
Bauer, G., et. al. 2018 [57]	Environmental Science & Technology	BEV and HEV SAEV fleets simulated for New York City based on taxi data using agent-based model. Measured role of range on: fleet size, cost, and location of charging locations required (as applicable)	No	BEV, HEV	No	No	Yes 10-100 mi.	Yes: 1,2,4,10	City: NYC NY, USA	No	No
Loeb, B., et al. 2018 [56]	Transportation Research Part C: Emerging Technologies	Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions. Explored the relationship between fleet size and charging infrastructure required	No	ICV, BEV	No	No	Yes: 100, 325	Yes: 1-10	City: Austin, TX, USA	No	No

Authors, year	Journal	Scope	VC: Vehicle Sensors?	VC: Powertrain(s)?	VC: SAV Controls?	VC: Component Energy Impacts?	FC: Vehicle Range?	FC: Compare Vehicle Capacity?	FC: Scope of Study	Grid Impacts?	Environmental Impacts?
Hyland, M., et al. 2018 [87]	Transportation Research Part C: Emerging Technologies	Studies SAEV operations for Chicago. Measures SAEV deployment performance for 6 strategies. Found a dependence on the waiting time, fleet size performance to service area	No	N/A	No	No	No	No	City: Chicago IL, USA	No	No
Brownell, C., et al. 2014 [79]	Transportation Research Board	Measures the fleet size and associated costs of two state-level autonomous vehicle networks in New Jersey	No	N/A	No	No	No	No	State: NJ, USA	No	No
Pernestål, A., et al. 2019 [63]	European Journal of Transport and Infrastructure Research	Review of 26 SAV/SAEV simulation studies, evaluated for methods and results, comparisons made between primary attributes (e.g., range, wait time, VMT, etc.)	No	Yes	No	No	Yes	Yes	Urban, City, State, Country	No	No
Forrest, K., et al. 2016 [80]	Journal of Power Sources	Uses HiGRID to measure GHG impacts resulting from various BEV charging protocols (i.e., immediate charging, smart charging, and V2G), for 2030 and 2050 Renewable Portfolio Standards (RPS)	No	BEV	No	No	No	No	State, CA	Yes: GHG	No
Tarroja, B., et al. 2015 [81]	Energy	Uses HiGRID to measure impacts of various vehicle powertrains, in large scale deployment, on California energy resource mixes and GHG emissions	No	PHEV, BEV, FCEV, PFCEV	No	No	Yes: (Var.)	No	State, CA	Yes: Mix, GHG	No

Authors, year	Journal	Scope	VC: Vehicle Sensors?	VC: Powertrain(s)?	VC: SAV Controls?	VC: Component Energy Impacts?	FC: Vehicle Range?	FC: Compare Vehicle Capacity?	FC: Scope of Study	Grid Impacts?	Environmental Impacts?
Wang, S., et al. 2019 [82]	Applied Energy	Evaluates several end-uses for excess renewable energy based on cost and GHG reduction using HiGRID	No	BEV, FCEV	No	No	No	No	State, CA	No	GHG
Hendrickson, T. P., et al. 2015 [83]	Environmental Research Letters	Performs a Life-cycle Analysus (LCA) on Plug-in Electric Vehicles in California, measures corresponding impacts, including GHG and CAP using GREET	No	BEV	No	No	No	No	State, CA	Yes	GHG, CAP
Huo, H., et al., 2009 [84]	Atmospheric Environment	Uses GREET to measure Well-To-Wheel CAP emissions for several different vehicle powertrains	No	ICV, HEV, BEV, FCEV	No	No	No	No	State, CA	No	CAP
Lajunen, A., et al., 2016 [88]	Energy	Performs LCA for various-powertrain busses, compares CO_2 emissions of each for Finland and California scenarios	No	ICV, HEV, BEV, FCEV	No	No	No	No	Country Finland State, CA	No	CO_2

3. Approach

3.1. Tasks

Task 1. Measure Vehicle-Centric Energy Impacts of SAEVs

This task measures the vehicle-centric impacts of SAEV technologies and is complete when a set of efficiency measures are garnered for a group of prototype SAEVs. This task starts with a literature review to establish the energy efficiency improvement potential for individual sensor technologies on non-autonomous vehicles. This will establish which sensor technologies have the greatest potential for efficiency improvement when these sensors are ultimately installed on prototype SAEVs.

After the literature review, a simulation framework to evaluate the energy, environmental, and traffic improvement of future vehicular technologies will be developed. This framework will allow the researcher to design individual SAEV prototypes (e.g., by varying powertrain, weight, drag, etc.) and design and test connected vehicle protocols (e.g., communication range, latency, vehicle speed profile, etc.) to measure the overall impact of vehicle re-sizing, eco-driving in a city scenario, platooning in a highway scenario, and other vehicle-centric energy opportunities on custom vehicles. This framework is used to garner results based on various SAEV architectures and can be updated with future vehicle performance metrics as ZEV and AV technologies continue to improve.

Task 2. Size and site SAEV stations for proposed deployment construct, and measure fleet-centric energy impacts of SAEVs

This task uses California Department of Transportation (Caltrans) model trip data to determine the capacities and locations of SAEV stations. The results of this task include a measurement of the VMT necessary to serve future trips of Californians within the parameters of a hypothetical neighborhood-SAEV (i.e., Nice-SAEV) program, as well as other SAEV-fleet metrics which vary depending on the prototypes used. Trip data are sourced from the Caltrans Short Distance Travel Demand Model (SDTDM), which was validated for the year 2010 and includes a 2050 forecast of all trips taken in California for a representative fall day. These trips are spatially allocated across 5,454 transportation analysis zones (TAZs), and each TAZ is weighted according to trip activity likely to be performed by SAEVs. These data are imported into ArcGIS, which is used to allocate concept SAV stations with current Park-and-Ride facilities as candidate sites.

With SAEV stations sized and sited, each SAEV prototype can be evaluated for relative fleet-centric impacts in terms of: total number of vehicles required per fleet, number of VMT, number of parking spaces required per SAEV station, number of charging/fueling-spaces required per station, and total energy consumed per day. Fleet-centric and vehicle-centric impacts are then used as inputs for Task 3.

Task 3. Measure Energy Grid, GHG, and CAP Impacts of SAEVs

This task uses the vehicle and fleet-centric measurements from Tasks 1 and 2 as the inputs to the California statewide energy grid model HiGRID and the well-to-wheel energy and emissions model GREET. The results of this task will be:

1) The measurement of projected California grid impacts using HiGRID, including: energy resource mixes, GHG emissions, and Criteria Air Pollutants (CAPs) corresponding to SAEV fleet deployments
2) The measurement of projected transportation sector impacts in terms of GHG and CAPs using the GREET model.

4. Measure Vehicle-Centric Energy Impacts of SAEVs

The overall objective for this task is to measure vehicle-centric impacts of SAEV technology, thus producing an efficiency measurement for a group of prototype SAEVs. This task starts with a literature review to establish the energy efficiency improvement potential for individual sensor technologies on non-autonomous vehicles. This will establish which sensor technologies have the greatest potential for efficiency improvement when these sensors are integrated with SAEVs. Some of the material from this section has been published in an article titled 'A Review of Sensor Technologies for Automotive Fuel Economy Benefits'. The copyright for this work belongs to SAE International © 2018 [89].

After the literature review, a simulation framework to evaluate the energy, environmental, and traffic improvement of future vehicular technologies will be developed. This framework will allow the researcher to design individual SAV prototypes (e.g., by varying powertrain, weight, drag, etc.) and design and test connected vehicle protocols (e.g., communication range, latency, vehicle speed profile, etc.) to measure the overall impact of vehicle re-sizing, eco-driving in a city scenario, platooning in a highway scenario, and other vehicle-centric SAV energy opportunities on custom prototype vehicles. This framework is used to garner results based on various SAV architectures and can be updated with future vehicle performance metrics as SAEV technologies continues to improve. Some of the material from this section has been published in an article titled 'A Planning Tool to Assess Advanced Vehicle Sensor Technologies on Traffic Flow, Fuel Economy, and Emissions'. The copyright for this work belongs to SAE International © 2018 [35].

4.1 Automotive Sensor Literature Review

Vehicle fuel efficiency can be enhanced when environmental signals in the near vicinity of the vehicle are better interpreted by drivers or by running control systems, whether a car is in stop-and-go traffic, approaching a lower speed zone, or approaching an intersection. Many sensor technologies can be integrated with a vehicle to aid in detecting environmental signals, though a wide range of technological capability, maturity, cost of integration, flexibility of being integrated with other sensor technologies, and robustness is required to detect environmental signals under various environmental conditions. This review addresses the advantages and disadvantages of various sensor technologies for their potential to enhance vehicular fuel economy.

The review is structured as follows. First, the review identifies (1) the environmental signals that can be detected to improve vehicular fuel efficiency and (2) the state-of-the-art sensor technologies that can be used to detect these signals. The review focuses on sensor technologies with a relatively strong promise as documented in previous academic works and collaborations with auto manufacturers and demonstration projects. Second, from this initial step, each sensor is analyzed for the potential to achieve an improvement in fuel economy and vehicular integration. Note that while the studies presented consistently measure efficiency impacts of standard internal combustion powertrain type, the fuel economy changes cited are indicative but not precise based on assumptions made.

4.1.1 Preliminary Review of Environmental Signals and Corresponding Sensor Technologies

The review begins with determining the environmental signals that are amenable to enhance fuel economy. Safety technology signals are considered as well. For example, vehicle response to safety-critical scenarios, such as preventing a forward collision, can be associated with vehicle efficiency scenarios, such as preventing excessive acceleration and deceleration. Therefore, the review begins with demonstration projects and academic publications which test and evaluate state-of-the-art technologies that mitigate major threats to both efficiency and safety.

4.1.1.1 Slowing or Stalled Vehicles

Slowing or stalled vehicles pose a safety risk to drivers, and the sensor technologies designed to preclude a frontal collision can also be used to mitigate the effects of excessive accelerations and decelerations. To this end, several research initiatives have evaluated sensor technologies to address slowing or stalled vehicles. For example, a "Grand Cooperative Driving Challenge (GCDC)," held in 2011, was designed to explore practical applications associated with Cooperative Adaptive Cruise Control (CACC) systems, namely, adaptive cruise control (ACC) systems with vehicle-to-vehicle (V2V) telemetry. Sensor technologies such as vehicular radar systems (VRS), camera systems (CS), Light Detection and Ranging (LiDAR) systems, and V2V communication options were evaluated [90]–[92]. While CACC systems were estimated to improve fuel economy by approximately 10%, the results of neither the 2011 GCDC nor a second GCDC in 2016 [93] published results validating this 10% estimate. While the GCDC held in 2016 continued an assessment of CACC, fuel saving was not emphasized as a principal focus [93].

A second example is the "Automotive Collision Avoidance System Field Operational Test" involving the National Highway Traffic Safety Administration (NHTSA) and the General Motors Company. Together, these entities investigated forward collision warning systems and ACC systems incorporating VCS and VRS for their ability to improve driver safety and user-friendliness [94]. A third example is the "Connected Vehicle Safety Pilot" lead by the U.S.

Department of Transportation (USDOT) and automakers to test V2V and V2I technologies in real-world scenarios for their ability to prevent crashes without distracting drivers [95].

A fourth example is the "CAR 2 CAR Communication Consortium" where over 12 major automakers collaborated to develop industry standards for an array of connected vehicle technologies such as V2V and V2I [96]. Finally, the "Crash Avoidance Metrics Partnership (CAMP)," a collaborative research initiative conducted by a number of automakers together with the National Highway Traffic Safety Administration (NHTSA), evaluated the capabilities of connected vehicle systems such as V2V and V2I to enhance driver safety in a multitude of driving scenarios [97].

4.1.1.2 Stoplights and Stop Signs

Stoplights and stop signs can create scenarios for fuel efficiency loss when signals change or the location of these signals is unknown to the driver. Research efforts offer insight into how these signals can work collaboratively with drivers and vehicular systems and to what extent travel efficiency can be improved. Research projects such as the "Cooperative Vehicle-Infrastructure Systems (CVIS)" have developed a real-world technological platform to enable data transfer between vehicles and the surrounding transit infrastructure with the goal of enhancing driver awareness and transportation efficiency [98].

The "Dynamic Information and Application for Mobility with Adaptive Networks and Telematics Infrastructure (DIAMANT)" project strived to meet similar goals with regard to using V2V and V2I technology to keep drivers informed of potentially changing traffic patterns [99]. The "Safe and Intelligent Mobility-Test Field Germany (simTD)" project performed a real-world test of connected vehicle technologies and determined ways to resolve technical issues surrounding V2I communication [100].

4.1.1.3 Weather Conditions

Weather conditions can play a significant role in the efficiency of a journey. Therefore, it is important for drivers to be aware of the optimal route to take. In this context, researchers have proposed real-time weather notification systems to inform drivers and running control systems by using various sensors placed both along roadways and within vehicles [101]. Such research enhances both safety and fuel economy. In particular, adapting vehicle speed to safely avoid hazards also enables vehicles to conserve fuel when approaching these hazards. Similarly, onboard VCS have been proposed to alert drivers of increasingly hazardous levels of precipitation, allowing drivers to adjust their speed sooner for safer and more efficient travel [102]. This concept has also garnered automaker support, where vehicles can anticipate changing traffic patterns resulting from changes in weather by retrieving weather data from local sources and passing data among vehicles using CACC systems [103].

4.1.1.4 Human-to-Vehicle Interaction

The influence of the human driver is the subject of study in both demonstration projects and the literature. Research in the human-to-vehicle interface has spanned many years and evaluated the relationship between human/machine interaction and the efficiency of vehicle operation [104]. Demonstration projects, such as the “ecoDrive project” and the “eCoMove project,” have evaluated the results of this research [44], [105].

After (1) reviewing demonstration projects for environmental signals and sensor technologies with a connection to fuel efficiency, and (2) investigating the research initiatives behind each sensor technology, the sensor technologies selected for the research reported herein are presented in Table 3 below.

Table 3: Environmental Signals and Associated Sensor Technologies

Environmental signal	Associated sensor technology
Slowing or stalled vehicles	CS
	VRS
	V2V
	V2I
Stoplights and stop signs	V2V
	V2I
Weather conditions	CS
	V2V
	V2I

Note that LiDAR and various human machine interface technologies are not included. As was briefly mentioned in 2.2.1 Autonomous Vehicle Overview, research on the integration of LiDAR systems into vehicles for fuel economy enhancement is not yet represented in literature as a stand-alone technology. Research activities, such as the GCDC and others, have evaluated vehicles with multiple sensors, including LiDAR, at once, but as of this writing, little research evidence is available to allow an adequate comparison of fuel savings potential relative to the sensors presented in this review [106]. Additionally, the focus for LiDAR has been primarily on the identification of obstacles, similar to a VRS, though with the visual obstruction weaknesses typical of a VCS. For example, LiDAR systems provide information on what type of object is nearby from a 360-degree view (similar to a system of cameras), but cannot interpret the characters on traffic signs or the status of traffic signals [107]–[109]. As with a VCS, LiDAR systems are vision-based in that they work on the exchange of light and would therefore not be able to perform in heavy rain, in fog, or in dusty conditions [23], [110], [111]. While LiDAR systems help provide a comprehensive source of information for applications such as autonomous vehicles, they do not provide information in support of the present research which

(1) concerns detection of the outside-of-vehicle environment for eliciting fuel economy improvements and (2) employs novel sensor integration strategies.

4.1.2 Automotive Sensor Fuel Economy Potential

This section identifies the fuel economy potential of sensors and potential sensor combinations introduced in the previous review and in 2.2.1 Autonomous Vehicle Overview. Specific conceptual situations which have been evaluated for their fuel savings potential are described for each sensor and compared.

4.1.2.1 Vehicle to Vehicle Communication Fuel Economy Enhancement Potential

V2V sensor technology enables a vehicle to have an awareness of the status (speed, position, acceleration/deceleration, etc.) of surrounding vehicles while also broadcasting the same information to surrounding vehicles [112]. The fuel economy benefits of installing these systems on standard powertrain vehicles are between 5 and 20%, depending on driving behavior, as evidenced by simulations estimating efficiency improvements from speed and distance data, as well as with on-vehicle testing with human drivers [113], [114].

V2V technology has promise to enhance vehicle fuel efficiency in ways similar to the promise of enhancing occupant safety. While the technology has the ability to alert for objects to avoid, it can also signal regenerative braking for traffic jams, stationary vehicles, or other potential hazards ahead [37], [115], [116]. In this regard, V2V technology has the potential to enhance Adaptive Cruise Control (ACC) systems and ultimately provide advanced “awareness” of situations where fuel can be saved and potentially where regenerative braking can be applied automatically for vehicles equipped with regenerative braking (e.g., FCEVS, BEVs, and Hybrid ICVs). Increasingly, ACC systems, which are currently radar-based, can obtain additional perspective of the vehicle’s surrounding environment, thus adding to the overall context of the driving environment. For example, sudden high traffic scenarios can be perceived sooner to minimize wasted fuel and to maximize the opportunity for regenerative braking. The concept of adding V2V technology to an ACC system (i.e.,, CACC) can improve fuel economy by preventing the traffic speed oscillations of stop-and-go traffic from occurring in the first place and by conserving fuel and storing energy when the vehicle encounters such situations [117].

Below are presented two novel ways of applying V2V technology which may not be directly associated with V2V but have merit of enhancing fuel economy while also illustrating V2V technological flexibility.

Concept 1: V2V Garnering Weather Information to Enhance Vehicle Perception

This concept builds on the idea of enhancing vehicular perception to include information on changes to weather on a route specifically using V2V sensor technology. This has been investigated in terms of safety, but also in the context of fuel savings where weather can have an impact on the optimal cruising speed and route for the vehicle. The weather information is sourced by vehicles informing other vehicles about weather conditions using onboard sensors [101], [102]. Note that automaker investment is being directed to developing weather-assisted vehicle communication systems in this context [103], [118].

Concept 2: Using V2V Data to Predict Vehicle Trajectories and More Efficient Routes

This concept involves processing raw V2V data to create direct, timely suggestions for the driver. One example is the provision of a fuel-efficient velocity profile for the driver to consider in driving situations such as stop-and-go traffic. Such information can account for up to 8% fuel economy enhancement for standard powertrain vehicles, as measured by optimal fuel usage simulations [119], [120]. The same concept could work in combination with an ACC system, where the throttle and braking movements are automatically controlled by the vehicle itself. While the ACC system would normally be subject to string instability, resulting in the uncoordinated velocity fluctuations of stop-and-go traffic, a greater environmental awareness for vehicular running control would reduce this effect [121]. Data from connected vehicles could also be used to suggest the most efficient route for the driver. While this concept has been investigated based on an aggregated pool of data from a centralized online source [122], the use of real-time V2V data directly from vehicles has not yet been addressed. As with the previous concept review, the concept of efficient routing and efficient vehicle trajectories is a focus of various automaker companies [123].

In summary, V2V technology has the potential to increase fuel efficiency in addition to passenger safety. The conventional applications of V2V technology alert the driver to upcoming traffic conditions or hazards, which in the fuel efficiency context enables the driver to proactively ease the throttle or engage regenerative braking. Depending on driver behavior, the fuel efficiency of the vehicle can be enhanced between 5% and 20% as evaluated on standard powertrain vehicles [113], [114]. V2V technology can also be integrated with an ACC system which could execute these functions automatically. Additionally, concepts have been investigated by automakers looking to apply V2V technology in other ways such as garnering and using weather information and projecting efficient vehicle trajectories to inform drivers and vehicles. These are concepts that also have merit in the fuel efficiency context, with conclusions of Concept 2 being an 8% fuel efficiency increase for standard powertrain vehicles [120]. V2V technology is relatively proven in the context of fuel economy enhancement compared to technologies such as VCS and VRS. Demonstration projects that test and evaluate V2V technology have shown the technology to be effective and economically feasible to install.

Domestically, NHTSA is supportive for mandatory V2V systems in vehicles. However, should a mandate be promulgated, a population of V2V-enabled vehicles must be deployed to have a meaningful impact on fuel efficiency. As an additional practical consideration, the costs associated with V2V technology are relatively low, estimated below $300 US per unit [112].

4.1.2.2 Vehicle to Infrastructure Communication Fuel Economy Enhancement Potential

The core technologies behind the data transfer are largely the same for V2V and vehicle-to-infrastructure (V2I) systems. However, with V2I systems, the data are transferred between vehicles and infrastructure sources such as traffic signals. This review covers how V2I technology enables a vehicle to utilize the surrounding infrastructure for a potential fuel economy benefit. The similarities and differences between V2V and V2I vary by application with each offering a particular benefit to fuel economy. For example, typical applications of V2V provide left-turn assistance (from knowing vehicle position), pre-collision warning (from knowing vehicle position and movement information), lane change warning (from knowing vehicle position), and emergency electronic brake light (which is an electronic emergency message that a stalled vehicle can send which cannot be obscured with fog or other visual limitations) [112]. On the other hand, some applications of V2I may include traffic signal warnings where, in the efficiency context, the vehicle can (1) activate regenerative braking systems when approaching a red stoplight, (2) communicate with the signal and change it prior to reducing speed, or (3) activate regenerative braking in a dangerous or reduced-speed curve ahead warning [112].

The following are applications of V2I which may not be immediately associated with V2I itself. These concepts have the merit of enhancing fuel economy while also demonstrating the technological flexibility of these sensors.

Concept 1: Vehicle-Traffic Signal Cooperation

A vehicle that stops at a red light and accelerates again produces up to four times the CO2 emissions of a vehicle driving at constant speed [124]. Preventing such situations would have significant impacts on vehicular fuel efficiency in addition to the emissions benefits. One way in which V2I can prevent this specific transportation inefficiency is by enabling traffic signals to broadcast their status to oncoming vehicles. If a vehicle is equipped with the necessary V2I and an ACC system, the vehicle will have an advanced perception of the signal status and apply the appropriate velocity curve [43]. The aforementioned research simulation, using an optimization-based control algorithm, explored the fuel savings potential in three example case studies and found that about 40% fuel savings can be accomplished by eliminating stop-and-go behavior at traffic lights when vehicles know in advance the signal status and duration of the signal status. Another V2I application was designed to relay information to intersection-bound autonomous vehicle traffic for eliciting greater traffic efficiency [125]. Impacts were measured using the VISSIM microscopic simulation package together with the EPA MOVES model for energy and emissions measurements. Results indicated that overall energy consumption could be reduced by 12-15% depending on traffic conditions and simulation parameters.

Demonstration projects such as CVIS have shown that this concept is supported with available technology and industry moving toward incorporating V2I in future vehicular fleets [126]. Current European research efforts continue the push for use of V2I in the ITS-Europe ecoDrive project, where fuel savings of up to 25% have been measured in computer simulations of representative traffic through an intersection.

Concept 2: Driver Awareness of Traffic Signal Status/Green Light Optimal Speed Advisory

A less complex application of V2I relies on the driver to prevent red light losses in fuel efficiency, resulting in approximately 10% fuel savings as tested on standard powertrain vehicles [127]. For example, approaching an intersection about 20 seconds of travel away, the driver receives two dashboard messages: the signal is red and the recommended speed with which to approach the intersection. Such systems could also display information on how long the traffic light will remain in a particular phase [127], [128]. This technology is also being investigated with automaker support in the context of safety as the part of a “Cooperative Intersection Collision Avoidance System (CICAS)” where, rather than displaying a message regarding an oncoming intersection and recommended velocity profile, the system provides an emergency alert to a driver approaching a dangerous intersection that may constitute a collision course with another vehicle [129].

In summary, V2I has much of the same merit to increase fuel efficiency as V2V through informing the driver of traffic conditions, traffic signal status, and optimal velocity profiles. In the literature, the increase in efficiency was found, from simulations, to range from 10% [127] to 40% [43] for standard powertrain vehicles. Like V2V technology, V2I technology can be integrated with an ACC system and perform more efficient driving behaviors automatically.

In terms of technological maturity, V2I is proven to enhance fuel economy. V2I is practical and effective with fuel efficiency increases on standard powertrain vehicles ranging from 15%, in the IntelliDrive project, to 25%, with the ecoDrive project. In terms of cost, similar relatively low in-vehicle costs for the "vehicle" component of V2I would be likely shared with V2V. However, equipment and installation costs associated with the "infrastructure" for V2I are expected to be relatively expensive, with estimates currently in the range of $15,000-$20,000 US per infrastructure communication point [130].

<u>4.1.2.3 Vehicular Camera System Fuel Economy Enhancement Potential</u>

VCSs can be installed into vehicles for the purpose of increasing fuel efficiency relatively easier, at lower cost, and operating with less technological complexity than V2V, V2I, and VRS [23], [131]. The following review addresses whether and the extent to which VCS can enable a vehicle to experience a fuel economy benefit. The manners by which VCS can integrate with other vehicular systems to provide a potential fuel economy enhancement are described as follows.

Concept 1: Automatic Regenerative Braking from Combined VCS and ACC Systems

VCSs such as those from Mobileye are installed to alert the driver to objects of interest on the road with the goal of maximizing safety [132]. The objects typically include approaching vehicles which are too close to the front of the vehicle (the alert would help prevent forward collisions and discourage risky behavior such as tailgating), LDW, and speed limit alerts. The VCSs ability to recognize traffic signs is one of the biggest advantages of the visual information-based system over other advanced driver assistance technologies, aside from relatively low cost and ease of installation. Additionally, unlike most approaches to V2V and V2I systems, VCSs are in deployment today for safety partial automation applications. In the context of fuel efficiency, a conventional VCS will alert the driver to reduce throttle position or to notify the driver to apply regenerative braking, depending on the situation. In the safety context, VCSs have already been shown to provide roughly a 3% increase in fuel efficiency for light-duty vehicles in the euroFOT project from testing standard powertrains [133]. However, in the fuel economy context, a more optimal system could be created which reduces speed and applies "Automotive Regenerative Braking (ARB)" automatically based on the information processed by the VCS. This more optimal system would consist of VCS to detect and process speed limit information working with ACC or a standard "Cruise Control (CC)" system to execute the change in speed automatically depending on the detected vehicles or traffic sign information.

The concept of an integrated VCS/ACC/ARB has not been reported. To indicate an industry movement on this concept, Tesla Motors Inc. has combined these technologies, but has yet to integrate traffic sign recognition with the ACC systems.

To summarize, VCSs are relatively inexpensive, are easy to install, and can interpret visually available information that would normally be detected by the human eye. Image recognition software is continuously improving, and, despite the state of the art being traffic sign recognition, one can imagine additional opportunities to use this technology as more visually available information can be interpreted and computing power becomes less expensive. While fewer direct demonstrations of fuel efficiency are available, VCS has proved useful in commercial vehicles for safety, and numerous accepted standards are in effect which indicate government acceptance for VCS deployment. Opportunities exist for VCSs to directly enhance fuel economy. For example, by adding a VCS to alert the driver of unsafe behavior, fuel efficiency has been shown in the euroFOT project to increase by 3% for standard powertrain vehicles. VCSs with the capability to detect traffic signs would likely have a greater fuel economy impact when integrated with an ACC. The costs associated with VCSs are relatively inexpensive when compared to other technologies, with optional vehicle safety packages with VCS and VRS together costing in the range of $1000-$2,000 US [109].

4.1.2.4 Vehicular Radar System Fuel Economy Enhancement Potential

The following section highlights VRS which, like VCS, are a mature technology in the safety context but garners information with value for enhancing fuel economy. This section also addresses combining VRSs and VCSs for system robustness and capacity to improve fuel efficiency. At the time of this writing, the search for conceptual applications yielded few novel VRS sensor integration strategies. While VRS have the potential to combine with other technologies (namely, VCS) to improve the overall robustness of environmental perception, applications of the technology to V2V and V2I are just emerging.

Concept 1: VRS Sensor Fusion Concept

In the context of fuel efficiency, VRSs act as a robust Forward Collision Warning (FCW) sensor where the leading benefit of a VRS is a relatively deep perception of oncoming hazards and changing traffic conditions. The driver of the vehicle can then make better informed decisions of such hazards and changes, resulting in safer and more efficient driving behavior, and an ACC system can act on this information automatically. Altogether, by “smoothing” vehicle velocity with VRS, up to 14% fuel economy savings have been measured in standard powertrain vehicles [61]. In optimal conditions, a VCS will suffice for this purpose while offering the capability to interpret visually available information, such as traffic signs. However, the merit of integrating a VRS in an advanced vehicle is that VRSs operate over a wider range of weather and road conditions and produce similar basic-object detection capabilities [134]–[137]. Yet, as the cited research indicates, substantial merit for radar systems to contribute toward the overall vehicular fuel efficiency is evident.

Overall, VRSs have been primarily applied to enhance safety, being that VRSs are capable of robustly detecting objects that may pose a threat to passenger safety. However, in the context of enhancing fuel efficiency, the information VRSs provide the driver or running control systems is similar to that of a VCS but without the capability to differentiate between objects or interpret traffic signs. In the context of integration strategies, VRS offer significant benefits in terms of robustness and are not subject to weather conditions and debris. In addition to providing information regarding nearby objects, VRS provide a baseline efficiency improvement that can be as high as 14% as measured for standard powertrain vehicles [61].

4.1.2.5 Summary of Sensor Fuel Economy Enhancement Potential

Connected Vehicle Systems (e.g., V2V and V2I) are evident in many successful demonstration projects and this technology is relatively mature compared to VCS and VRS technologies. There is also support from domestic policy, which indicates an eventual mandate of this technology in the US. V2V systems can improve fuel economy of standard powertrain vehicles by as much as 20%. However, these systems rely on other vehicles to be equipped with the same technology for there to be an improvement to fuel efficiency. Because of the high potential to improve fuel economy, V2V technology is selected as a focus of greater study for the future sections of this research. V2I systems are technologically similar to V2V and share much of the maturity of V2V systems. This technology has the potential to improve fuel consumption by as much as 25% for standard powertrain vehicles, thus demonstrating a high potential to improve fuel economy, and is therefore studied in greater depth in this research.

Vehicular Camera Systems are very mature in the context of enhancing passenger safety and can be found in contemporary vehicles. Advances in image processing allow this technology to interpret street signs, which could either be used to alert the driver of changing speed limits or otherwise automatically reduce speed or apply regenerative braking when integrated with the running control of the vehicle in an adaptive cruise control system. A drawback of VCS is that the camera system relies on visually available information which can be obscured by weather conditions or dust/dirt near the lens. VCSs are a quite promising technology for enhancing efficiency in the very near-term, but they are not considered when designing the connected mobility model for this work.

Vehicular Radar Systems have been installed on most vehicles which have frontal collision avoidance systems and adaptive cruise control systems. VRSs are not as sophisticated as camera systems in terms of technological capability, though they are relatively robust, and have potential for providing efficiency improving information. A potentially strong VRS application would be to support VCSs. Ultimately, despite the described merit, these VRSs are not considered to be as promising as the 20-25% V2X benefits when designing the connected mobility model.

4.2 Designing FETCH, the SAEV Vehicle-Centric Energy Impacts Model

The study of environmental signals and sensor technologies concluded that V2V and V2I could offer the greatest fuel economy benefits, by making such controls as eco-driving and platooning possible, according to the research listed in 2.3.1 Vehicle-Centric Energy Impacts. As mentioned in Section 2.3.1, vehicle-centric energy impacts relate not just to the vehicle driving behavior (e.g., eco-driving), but also to the vehicle design itself (e.g., weight, aerodynamic drag, powertrain choice, and general re-sizing effects).

This section provides evidence to select the most appropriate simulation tools to measure both aspects of vehicle-centric energy impacts to better understand the possible vehicle-centric energy impacts with SAEV technology. Each type of tool is covered separately (vehicle design, traffic, network, emissions), and the reason for the tool selection is described. Pros and cons tables are used to clearly communicate the advantages and disadvantages of each simulation tool option.

4.2.1 Vehicle Design Tool Selection

Vehicle design parameters such as powertrain choice, weight, and aerodynamic drag all have an impact on the energy efficiency on a vehicle. SAEVs are not yet in production with only brief glimpses into what their design and energy efficiency may portend. Fortunately, simulation tools are available for researchers to measure how energy efficient these futuristic vehicles might be. Such tools are explored and evaluated for their ability to accomplish the research objective. Some important factors to consider are: widespread use (for easy comparison of results to similar studies), ability to perform comparison of different driving profiles (to compare standard and eco-driving behavior), lack of a mandatory license (to aide in the sharing of the tool and capability), and general approachability (an accessible user experience will allow more researchers to perform comparison studies). Simulation tools frequently share the same parameters, and unless noted otherwise, each tool in the table below has: the ability to select powertrain (ICV, HEV, BEV, and FCEV options), a free license, and the ability to choose a driving profile for comparison of eco-driving behavior:

Table 4: Vehicle Design Simulation Tools, Pros and Cons

Tool Name	Pros	Cons
FASTSim	Relatively high number of recent academic publications [138]. Relatively approachable Excel and Python interfaces, training not necessary for operation.	Fewer parameters to adjust compared to commercial options
Autonomie	Relatively detailed (large number of inputs to model and parameters to adjust for accuracy) [139], relatively wide industry usage [140]	License required unless for "DOE-funded activities and other specific purposes" [140]. Less approachable.
MOVES	Similar research projects have used MOVES to accomplish goals [141], relatively high computational power [142]	Low number of parameters to select, relatively incapable of designing custom vehicles as model uses estimates of existing vehicles. Limited powertrain options

The software capability (e.g., powertrain selection and custom parameters) of Autonomie and the Future Automotive Systems Technology Simulator (FASTSim) were found relatively strong compared to MOVES. Both FASTSim and Autonomie are employed by numerous organizations. However, the open operating license and general approachability of FASTSim are the reasons for its selection as the vehicle-design component of the FETCH model.

4.2.2 Traffic Simulation Tool Selection

Like many simulation tools, the various traffic simulation tools were found to share many similar criteria. In order to clearly see the outstanding pros and cons to these tools, only the unique criteria are listed in the table. The common characteristics are listed outside of these tables to prevent redundancy. Unless otherwise noted, these tools all share the following features: free or open source, allows for integrating other tools without altering source code, validated in numerous research initiatives. More details are described in the table below.

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Table 5: Traffic Simulation Tools, Pros and Cons

Tool Name	Pros	Cons
SUMO	Frequently used for V2I simulation [143] Chosen for relevant previous uses / larger user base / more available support for independent researchers [144]	
AIMSUN	Model shown to calibrate well with real traffic data [145]	License required
PARAMICS	3D visualization Tools [146]	License required
DIVERT	Can be integrated with NS-3, EMIT, at code level [147]	
VISSIM	Highly realistic bicycle, motorcycle, and pedestrian modelling, car following gap model used is relatively flexible (allows for more accurate representation of V2X effect on traffic), More suitable than PARAMICS and AIMSUN for small networks with complex geometry, traffic, and control strategies [148]	Less suitable than PARAMICS or AIMSUN for modelling large networks with many route choices. Expensive License.

Using a traffic simulation model with a great amount of user support and documentation would be necessary to accomplish the research goals of this project. Additionally, the model would ideally have been proven to be useful for many various scalable V2X studies, but it is not necessary to scale the simulation across a large city or state-wide. Finally, the lack of license would mean that this project could be more easily replicated and potentially shared by researchers. These reasons are why SUMO was chosen to be the traffic model to support the completion of the research objective.

4.2.3 Network Simulation Tool Selection

Using a selection process similar to the vehicle design and traffic simulation tools, the network simulation tools are organized next to the pros and cons for each tool, with the common features described separately. Unless otherwise noted, these tools all share the following features: free or open source, and capability of simulating contemporary V2X networks according to DRSC/WAVE standards. Please refer to Table 6:

Table 6: Network Simulation Tools, Pros and Cons

Tool Name	Pros	Cons
OMNET++	Realistically supports current V2X standards (IEEE 802.11p and IEEE 1609.4 (DSRC/WAVE), accounts for noise, building interference etc. [15]	
NS-2		Does not have IEEE 802.11p standard [15]
NS-3	Has 802.11p standard [14]	

User support, documentation, and a proven track record of various scalable V2X studies are essential to the selection of the network simulator, similar to the selection of the traffic model. The fact that OMNET++ supports these points, and supports an array of wireless networking standards, means that OMNET++ is the best model suitable for the research at hand.

4.2.4 Combined Traffic and Network Simulation Tool Selection

Another category of research tools are those for combined traffic and network simulation. Being that a traffic and a network simulator are both necessary components to satisfy the hypothesis, some tools offer a complete package that can be used to simulate V2X communication without requiring assembly. The integrated traffic and network simulation tools are organized next to the pros and cons for each tool, with the common features described separately. Unless otherwise noted, these tools all share the following features: fully integrated simulation platforms, full "communication" between simulation tools, options of traffic simulator and network simulator already determined. More details are described below in Table 7:

Table 7: Combined Traffic and Network Simulation Tools, Pros and Cons

Tool Name	Pros	Cons
VEINS (SUMO+ OMNET++)	Benefits of SUMO and OMNET++, large user base [146], Allows for some flexibility with future potential V2X technologies, such as 4G-LTE [149]	4G-LTE Capability requires Linux-based simulation framework
VSimRTI (VISSIM-SUMO, OMNET++/NS-3, PHEM)	Entirely integrated traffic, network, and emissions models. Professional support, integrated with more simulator options than most other choices, has greater simulation flexibility [150]	Does not allow for future technologies as well, costs ~$8600 though other pricing options are available.

The fact that VEINS combines the benefits of SUMO and OMNET++ and supports users with documentation and removes a traffic and network simulator integration step, VEINS was chosen as the best model to support this research. Note that this decision does not supersede the previous conclusions for choosing SUMO and OMNET++ but solidifies the decision with the additional benefits of an integrated simulator.

4.2.5 Summary of Vehicle-Centric Energy Impacts Simulation Framework

The simulation tool *FETCH* is designed to allow researchers to measure the vehicle-centric energy impacts of SAEV technology. Researchers can create a new vehicle design and alter the way the vehicle drives via V2V or V2I communication. Figure 15 below illustrates the inputs, outputs, and relative operation of this FETCH tool.

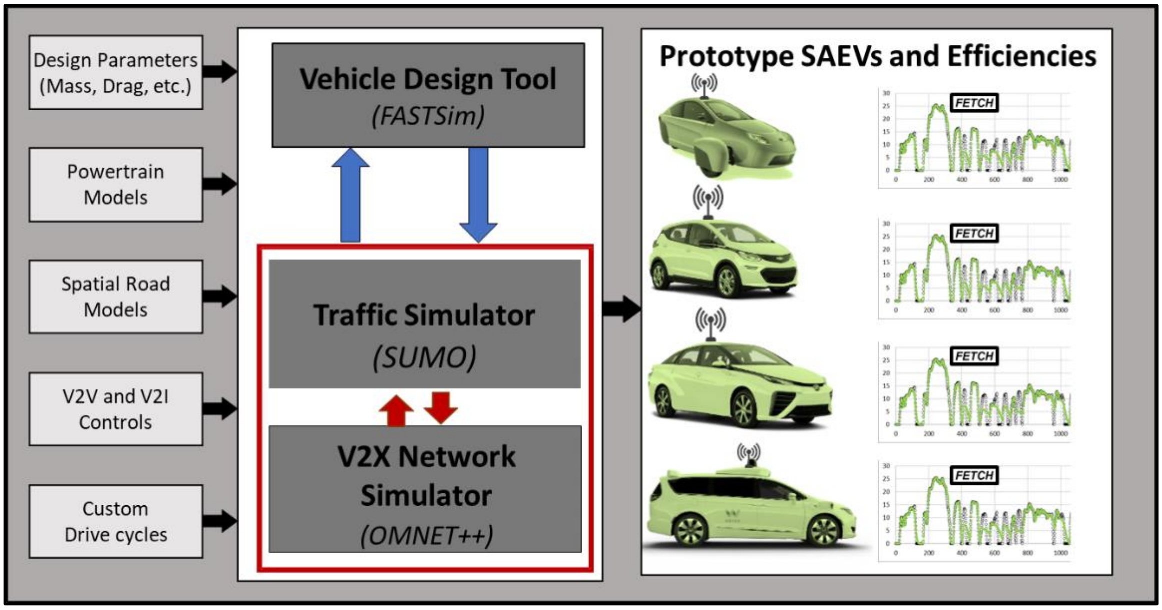


Figure 15: FETCH Tool Schematic

4.3 Using FETCH to Measure Vehicle-Centric SAEV Energy Impacts

This section describes the implementation of the FETCH tool to measure the energy efficiency of prototype SAEVs.

4.3.1 Prototype SAEV Designs

Prototype SAEVs are designed to reflect various capacities (i.e., 1, 4, or 8 seat vehicles), EV powertrains (i.e., BEV and FCEV), and two directions of autonomous vehicle technology installations (i.e., discrete low-profile installations as seen with modern Tesla vehicles, and the more prominent high-profile installations seen with Waymo vehicles). This work reflects present technological performance of these many technologies, and this research framework is amenable towards future refinements should researchers choose to re-visit SAEV energy impacts as technologies progress.

Several categories of vehicle are considered: Micro-SAEV (for 1 occupant), Medium-SAEV (for up to 4 occupants), and Large-SAEV (for up to 8 occupants). Each size-category of SAEV is converted to an EV powertrain if necessary, as scaled from modern production vehicles. An overview of the two sensor installation concepts, which will be installed on the prototype SAEVs in their respective sections, is shared first below.

4.3.1.1 SAEV Sensor Installations

While automotive sensor technology offers the potential for energy savings, the technologies themselves require energy to operate or affect the energy consumption of the SAEV in other ways. For this work, parameters such as vehicle weight, drag, and auxiliary power are altered to more accurately reflect the installation of various SAEV technologies on each SAEV prototype. The sensor installations can either be small or large-installations, as these are two general approaches to installing SAEV technology on contemporary autonomous vehicles.

Low-Profile SAEV Sensor Concept

The low-profile sensor installation concept is based on the present-day approach towards autonomous technology taken by Tesla brand automobiles as illustrated in Figure 16 below.

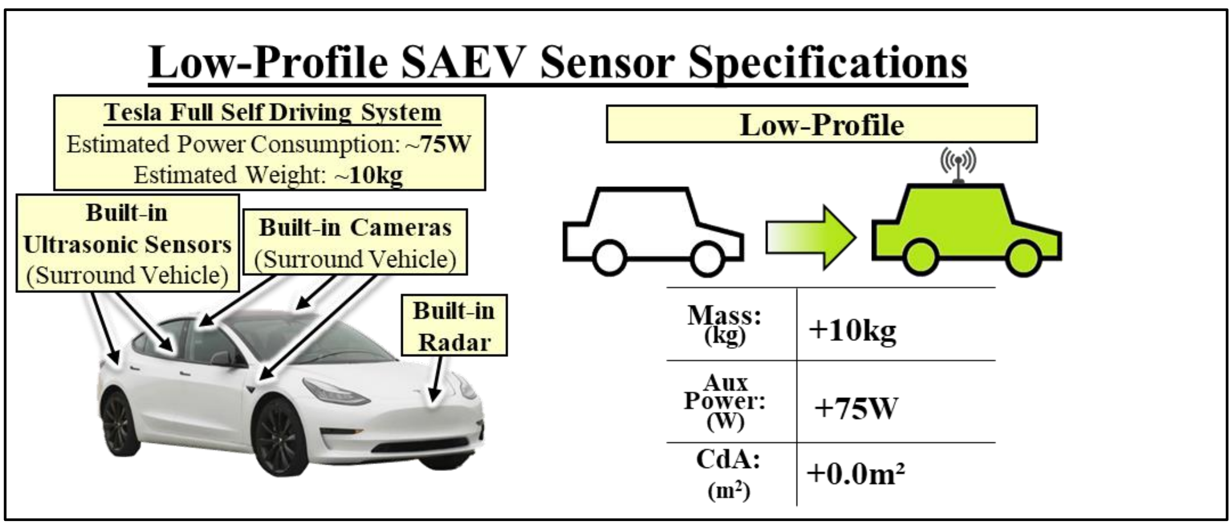


Figure 16: Low-Profile SAEV Sensor Installation Specifications

Note that the *CdA* value of 0.0m^2 represents the fact that there is no change in drag coefficient (i.e., *Cd*) nor a change in the front cross-sectional area (i.e., *A*) of the vehicle with the small sensor installation. The estimations for power are based on the reported power consumption of the Tesla FSD product, as described in a recent product launch [151]. The estimation for mass is an estimate of the mass of individual sensors plus computational equipment plus miscellaneous wiring.

High-Profile SAEV Sensor Concept

Another approach towards achieving self-driving capability is to install a relatively comprehensive suite of sensors mostly on the outside of the vehicle, as seen with contemporary autonomous vehicles such as those from Waymo, illustrated below in Figure 17.

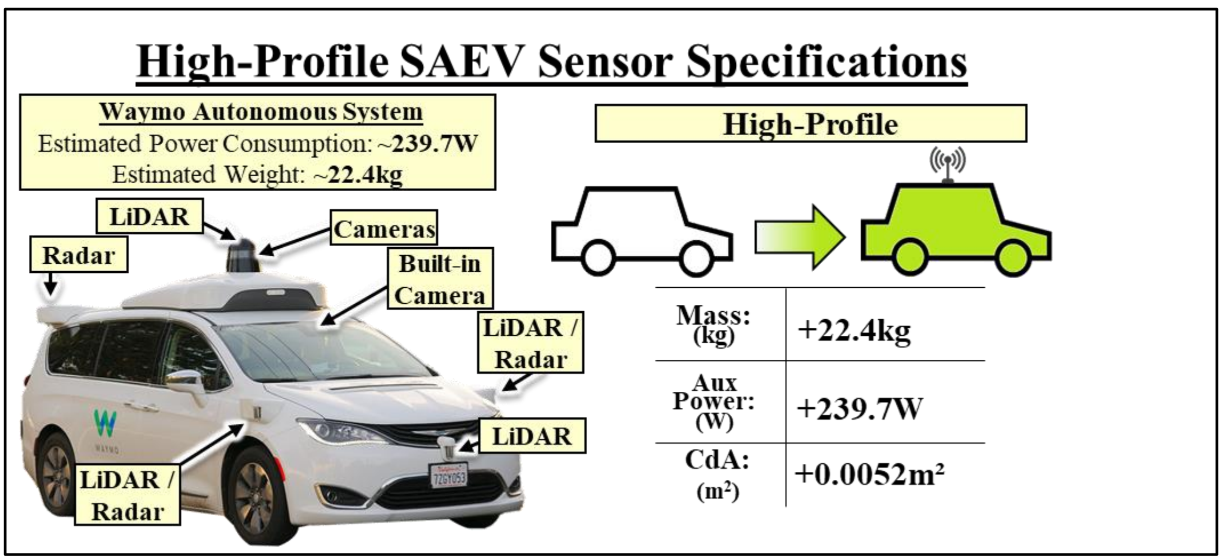


Figure 17: High-Profile SAEV Sensor Installation Specifications

The high-profile sensor concept has been explored by researchers who have estimated weight and power consumption parameters, which are found to be 22.4kg and 239.4W respectively [106]. The *CdA* value for this concept was calculated assuming that the additional VRS and LiDAR sensors on the sides and top of the SAEV concept are the same approximate *Cd* as driver side mirrors (i.e., the SAEV-sensors would have a similar, non-area-dependent, “slippery-ness” through the air), which was found to be approximately 0.017 in previous work [152]. To account for the total *Area* of the sensor installation, a sample enclosure was designed to approximate what would be required to protect the sensors on the top of the vehicle. The *CdA* is then estimated by summing the total *Area* of sensors and protective equipment and multiplying this by the *Cd*, as illustrated in Figure 18. This sensor *CdA* is then added to the *CdA* of each base prototype SAEV as an estimation of the total *CdA* of a high-profile sensor-equipped SAEV. Note that it is a simplifying assumption that the *CdA* of the vehicle and the *CdA* of the sensor package are directly additive. Ideally, the total *Cd* of each high-profile sensor prototype vehicle would be empirically measured with the sensors installed, using either wind tunnel testing or simulation tools such as computational fluid dynamics (CFD) software. Further information is described in the Future Work section.

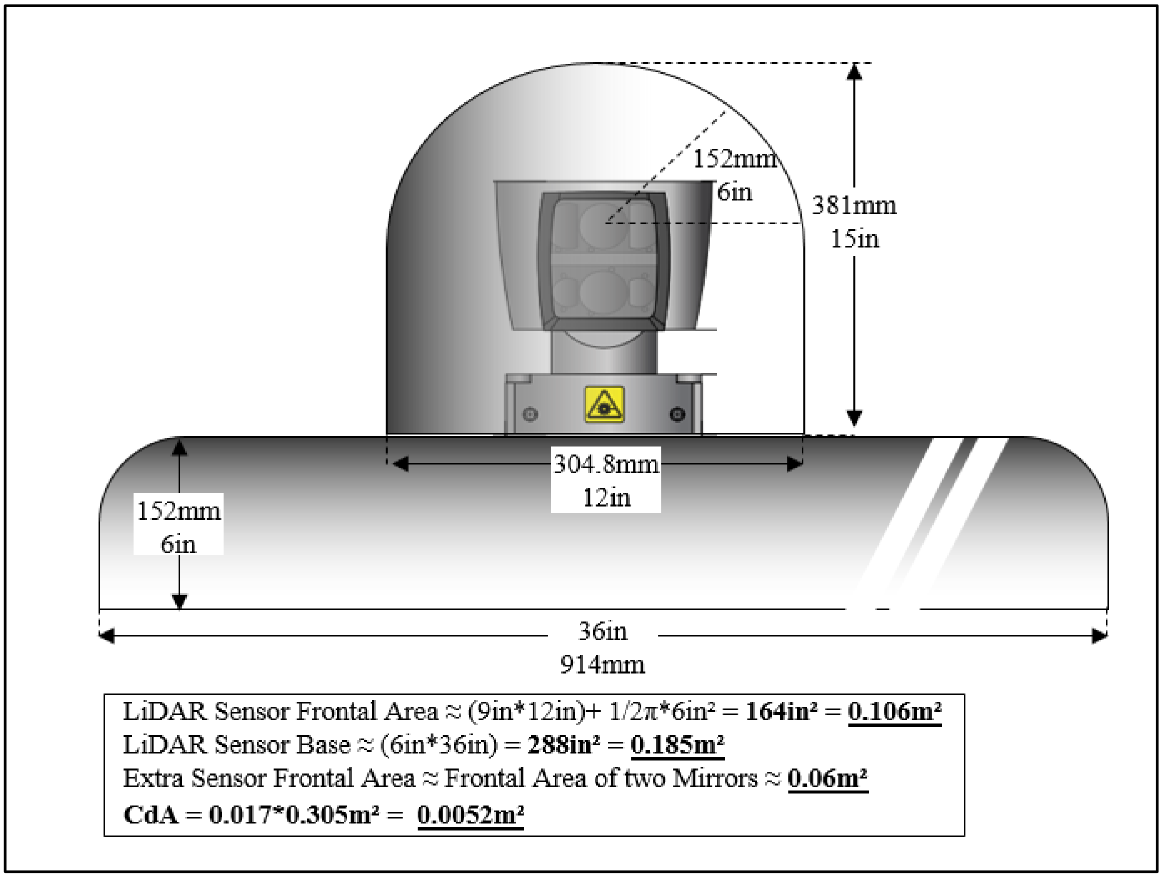


Figure 18: High-Profile Sensor Enclosure and CdA Calculation

4.3.1.2 Micro-SAEV Prototype Designs

As mentioned in the introductory sections of this work, most California commuters travel alone and in sedans that can carry up to 5 people. With a SAEV paradigm, a commuter wanting to travel alone could order up a vehicle sized just right for them. Indeed, just as ride-sharing products allow users to order medium and large-sized vehicles which are correspondingly priced, the possibility for a small and cheap one-seat private SAEV might be an appealing option for the future commuter. To serve this role, a Micro-SAEV has been designed from the Elio P4 pre-production ICV [153]. The design parameters of the Elio are then used as inputs for the FASTSim vehicle design software and real-world and simulated fuel economy measurements can then be compared as illustrated below.

Type:	PT:	CdA: (m²)	Glider Mass: (kg)	Aux. Power (kW)	Weight (kg)
Base	ICV (0.9L)	0.26	164	0.9	610

FASTSim Results

	Measured	FASTSim	Error (%)
City MPG	49	50.1	2.2%
Highway MPG	84	81.3	-3.2%
Combined MPG	**60.3**	**60.6**	**0.4%**

Figure 19: Micro-SAEV Base Vehicle, Elio ICV, Parameters and FASTSim Results

This ICV provides the base vehicle from which the Micro-SAEVs will be built. Note that the FASTSim measured ICV efficiency comes close to approximating the real-world measured combined fuel economy of the Elio vehicle. The low and high-profile (LP and HP, respectively) sensors are then added to this ICV to give insight into how they affect the energy efficiency without their possible energy efficiency improvements resulting from improved driving behavior. For the case of the Elio ICV (i.e., just a "SAV"), the added mass, size, and direct power-consumption of these sensors was found to have the expected negative effect.

SAV

Type:	PT:	CdA: (m²)	Glider Mass: (kg)	Aux. Power (kW)	Weight (kg)
LP Sensors	ICV (0.9L)	0.26	174	0.975	620
HP Sensors	ICV (0.9L)	0.265	186.4	1.14	632.4

	Base	ICV SAV (LP Sensors)	Change (%)	ICV SAV (HP Sensors)	Change (%)
City MPG	50.1	48.9	-2.4%	46.5	-7.2%
Highway MPG	81.3	79.9	-1.7%	77.0	-5.3%
Combined MPG	**60.6**	**59.2**	**-2.2%**	**56.6**	**-6.6%**
Range	**480**	**469**	**-2.3%**	**449.0**	**-6.5%**

Figure 20: Elio ICV-SAV Concept, Relative Effects of Low and High-Profile Sensors on Performance

Note that the *Base* vehicle above in Figure 20 shows the FASTSim results garnered from Figure 19 for a direct comparison. The *Change %* values of the low and high-profile sensor installations are relative to this *Base* MPG measurement. One can see that the effect of these sensors is a small to moderate decrease in fuel economy performance, as these sensors are not yet measured for their ability to improve fuel economy through their driving behavior controls. Knowing which sensors contribute to the significant efficiency losses is critical for efforts to proactively design efficient vehicles. For the ICV-Elio illustrated above, a Large-Sensor configuration of this vehicle is outfitted with constituent components one-at-a-time, (i.e., just weight, just drag, and just power consumption) to provide this information, shown below. Note that the sum of these individual efficiency-reduction values will add up to the total value listed in the figure directly above, aside from a potential ~1% rounding error.

ICV Elio	Base	SAV (+"Large Drag")	Change (%)	SAV (+"Large Mass")	Change (%)	SAV (+"Large Pwr")	Change (%)
City MPG	50.1	50.1	0.0%	49.6	-1.0%	47.0	-6.2%
Highway MPG	81.3	80.9	-0.5%	80.6	-0.9%	78.0	-4.1%
Combined MPG	**60.6**	**60.4**	**-0.3%**	**60.0**	**-1.0%**	**57.2**	**-5.5%**
Range	**480**	**479.0**	**-0.2%**	**476**	**-0.8%**	**454**	**-5.4%**

Figure 21: ICV Micro-SAEV Sensor-Level Energy Impacts

The base FASTSim design software is now employed to exchange the Elio ICV powertrain for BEV and FCEV powertrains. Basic design parameters are estimated using existing powertrain technology found with contemporary, commercially available Tesla BEV and Toyota FCEV powertrains. These estimates provide a reasonable placeholder for the performance characteristics (e.g., weight, range, acceleration, etc.) of SAEVs prior to their eventual deployment and availability for efficiency testing. For the BEV powertrain, the 2019 Tesla Model S P100 powertrain was scaled to a quarter of the 102.4 kWh capacity to provide 25.6 kWh for the Micro-SAEV prototype vehicle, as illustrated below [154].

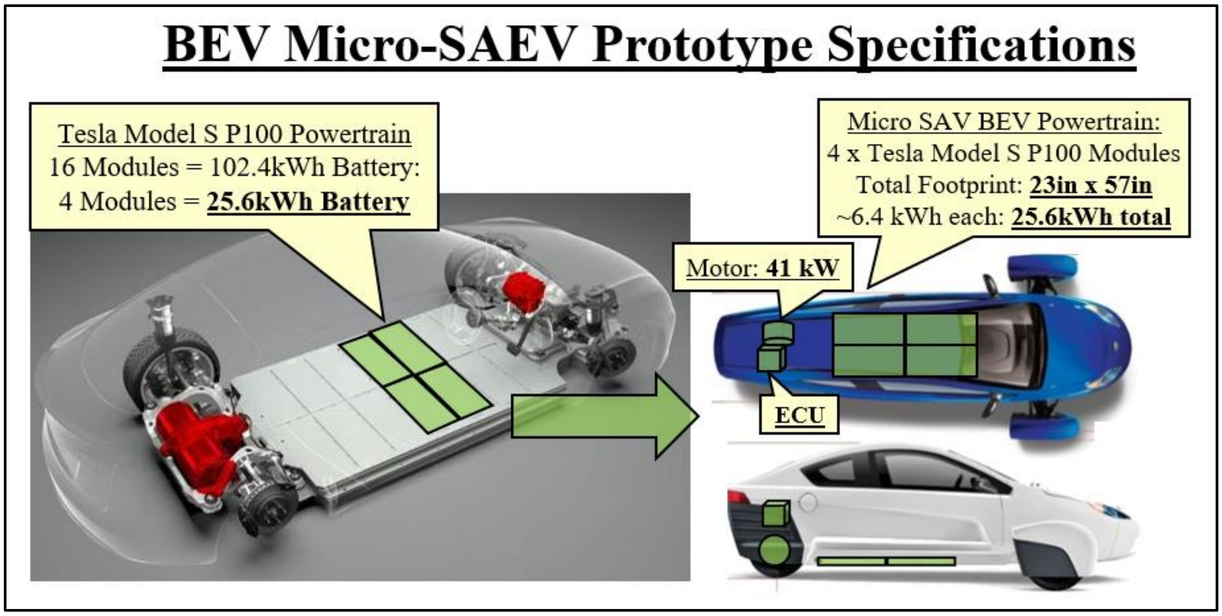


Figure 22: BEV Micro-SAEV Prototype Specifications

Note that the footprint of the four Tesla battery modules occupies an approximate area within the cabin space of the Micro-SAEV. Similarly, note that the 41kW motor of the Micro-SAEV produces the same power output as the ICV Elio provided. This electric motor was found to offer acceptable performance (i.e., acceleration from 0-60 MPH in 10.8 seconds) for the heaviest Micro-SAEV case tested. The motor, ECU, and other miscellaneous BEV powertrain equipment was assumed to be of a volume comparable-or-less-than the volume occupied by the ICV powertrain, as has been possible with many contemporary ICV-to-BEV retrofits and prototypes (e.g., 2012 Scion iQ-BEV). Please refer to Figure 23 below for the details on the performance of the BEV Micro-SAEV.

BEV-SAEV

Type:	PT	Battery (kWh)	Range (Miles)	Weight (kg)
LP Sensors	41kW	25.6	135	939
HP Sensors	41kW	25.6	126	952



	Base	SAEV (LP Sensors)	Change (%)	SAEV (HP Sensors)	Change (%)
City Efficiency (kWh/mi)	0.180	0.186	-3.3%	0.199	-10.6%
Highway Efficiency (kWh/mi)	0.150	0.152	-1.3%	0.159	-6.0%
Combined Efficiency (kWh/mi)	**0.167**	**0.171**	**-2.4%**	**0.181**	**-8.4%**
Range	**138**	**135**	**-2.2%**	**126**	**-8.7%**

Figure 23: BEV Micro-SAEV Prototype Performance Characteristics

The efficiency of the prototype BEV Micro-SAEV is favorable, even with high-profile sensors, when compared to the most efficient commercial BEVs available as of 2019. The 2019 Tesla Model 3 Standard Range Plus and 2019 Hyundai Ionic Electric each share a 0.25 kWh/mile rating from the US Department of Energy [155]. While not a vehicle with a range of upwards of 300 miles like certain BEV options available, this Micro-SAEV prototype is likely to be adequate for fulfilling the role of an autonomous shuttle for commuters. To revisit a study mentioned earlier, BEV-SAEVs with ranges between 50 and 90 miles were found to perform adequately in serving New York City taxi trips, given a network of Level 2 in various scenarios [57]. While the BEV Micro-SAEV may not be the best suited option for all of California, it may have merit in the service of dense urban areas. For reference, the additional sensor components on this vehicle have the energy impacts listed below.

BEV-SAEV

BEV Elio	Base	SAV (+"Large Drag")	Change (%)	SAV (+"Large Mass")	Change (%)	SAV (+"Large Pwr")	Change (%)
City Eff. (kWh/mi)	0.180	0.181	-0.6%	0.181	-0.6%	0.198	-10.0%
Highway Eff. (kWh/mi)	0.150	0.151	-0.7%	0.151	-0.7%	0.157	-4.7%
Combined Eff. (kWh/mi)	**0.167**	0.167	**0.0%**	0.167	**0.0%**	**0.179**	**-7.2%**
Range	**138**	**138**	**0.0%**	**138**	**0.0%**	**128**	**-7.2%**

Figure 24: BEV Micro-SAEV Sensor-Level Energy Impacts

The FCEV Micro-SAEV is based on a similarly scaled-down 2017 Toyota Mirai FCEV, as illustrated below.

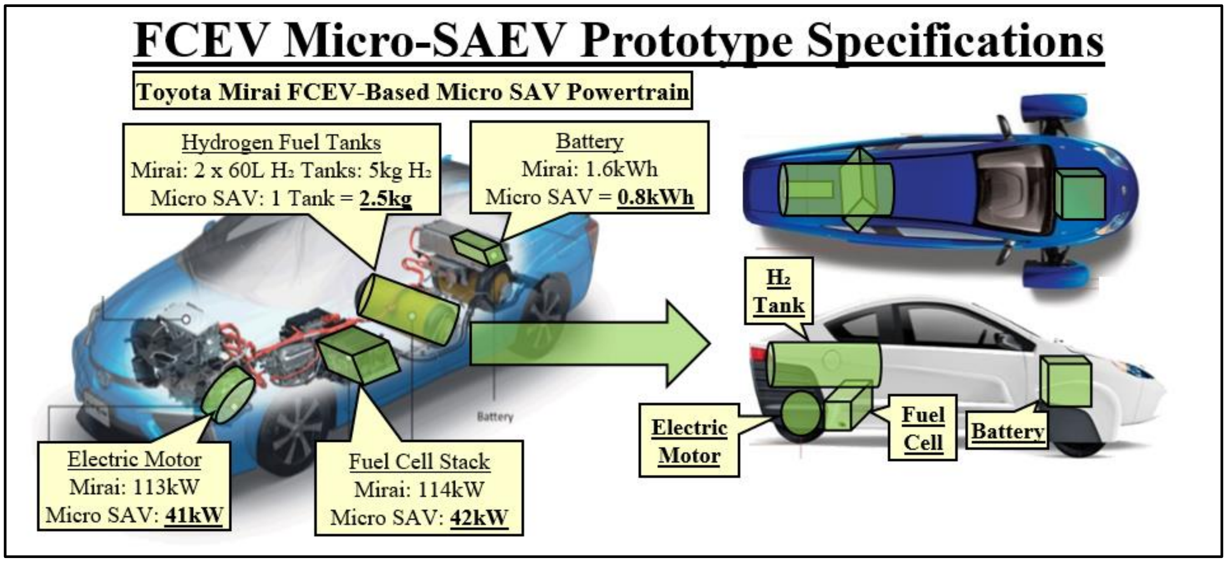


Figure 25: FCEV Micro-SAEV Prototype Specifications

The prototype FCEV Micro-SAEV sizes the Mirai equipment enough such that it will be able to provide the electricity to power the same 41 kW motor as with the BEV prototype. Thus, the fuel cell stack is reduced significantly, as are the fuel tanks and battery. As with the BEV prototype, it is assumed that removing the ICV powertrain and associated components will provide enough space for the FCEV powertrain. The performance details of the FCEV Micro-SAEV is shown in Figure 26 below.

Type:	PT	Tank (kg)	Range (Miles)	Weight (kg)
LP Sensors	41kW	2.5	217	737
HP Sensors	41kW	2.5	208	749

	Base	SAEV (LP Sensors)	Change (%)	SAEV (HP Sensors)	Change (%)
City MPGGE	78.8	77.4	-1.8%	73.8	-6.3%
Highway MPGGE	102.9	101.7	-1.2%	98.8	-4.0%
Combined MPGGE	**88.1**	**86.7**	**-1.6%**	**83.3**	**-5.4%**
Range	**220**	**217**	**-1.4%**	**208**	**-5.5%**

Figure 26: FCEV Micro-SAEV Prototype Performance Characteristics

Note that the range of the FCEV Micro-SAEV concept is greater than the range of the BEV counterpart. This is a performance characteristic typical of contemporary BEVs and FCEVs, where the BEV is using lithium-ion battery technology and the FCEV is using a hydrogen fuel cell. As with the BEV Micro-SAEV, this FCEV SAEV also has a favorable efficiency when compared to commercially available vehicles. For example, the 2019 Honda Clarity and the 2019 Toyota Mirai each achieve approximately 68 Combined MPGGE [156]. The sensor-level impacts for this prototype are illustrated directly below.

FCEV-SAEV

BEV Elio	Base	SAV (+"Large Drag")	Change (%)	SAV (+"Large Mass")	Change (%)	SAV (+"Large Pwr")	Change (%)
City MPGGE	78.8	78.6	-0.3%	78.4	-0.5%	74.3	-5.7%
Highway MPGGE	102.9	102.4	-0.5%	102.7	-0.2%	99.6	-3.2%
Combined MPGGE	**88.1**	87.8	**-0.3%**	87.7	**-0.4%**	83.9	**-4.7%**
Range	**220**	**219**	**-0.5%**	**219**	**-0.5%**	**210**	**-4.5%**

Figure 27: FCEV Micro-SAEV Sensor-Level Energy Impacts

4.3.1.3 Medium-SAEV Designs

The Medium-SAEV prototypes are based on existing 4-seat EVs, namely the 2017 Chevrolet Bolt BEV and the 2017 Toyota Mirai FCEV. These vehicles were simulated in the FASTSim tool for baseline performance measurements, which are shown below.

BEV

FCEV

Type:	PT	CdA (m^2)	Glider Mass: (kg)	Aux. Power (kW)	Weight (kg)
Stock Bolt	BEV	0.745	648	0.25	1758
Stock Mirai	FCEV	.752	1172	0.15	1930

FASTSim Results

Chevy Bolt	Actual	FASTSim	Error (%)
City Eff. (kWh/mi)	0.234	0.231	-1.2%
Highway Eff. (kWh/mi)	0.272	0.275	1.1%
Combined Eff. (kWh/mi)	**0.250**	**0.251**	**0.6%**
Range	**239**	**237**	**-0.8%**

Toyota Mirai	Actual	FASTSim	Error (%)
City MPGGE	67	68.6	2.4%
Highway MPGGE	67	65.1	-2.8%
Combined MPGGE	**67**	**67.0**	**0.0%**
Range	**312**	**312**	**0.0%**

Figure 28: Medium-SAEV Baseline Performance Measurements

These vehicles are then adjusted for the same low and high-profile sensor technology installations and measured for relative performance using the FASTSim tool. Illustrations of BEV and FCEV Medium-SAEVs are shown below in Figure 29 and Figure 30 respectively.

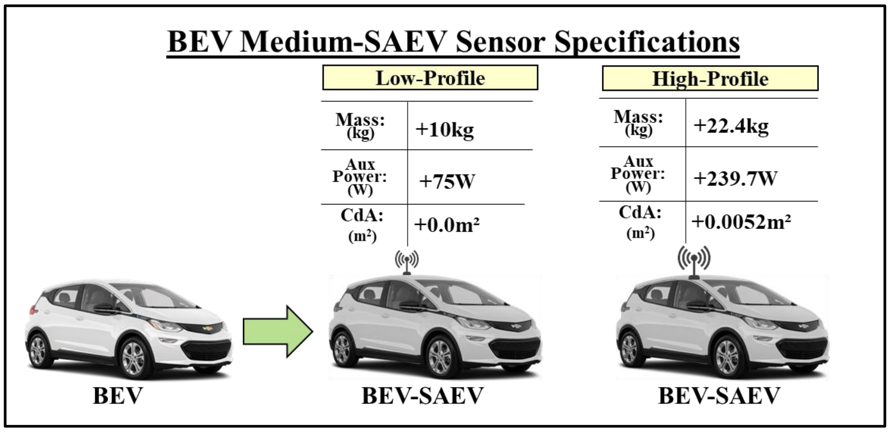


Figure 29: BEV Medium-SAEV Sensor Specifications

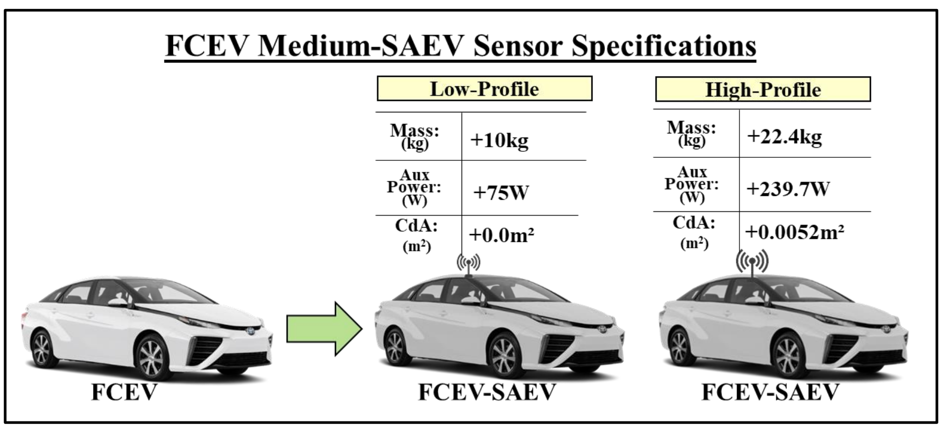


Figure 30: FCEV Medium-SAEV Sensor Specifications

While the same concept sensor suites are integrated, the sensors affect the Medium-SAEVs differently than the Micro-SAEVs. The results for the BEV Medium-SAEV are shown below in Figure 31.

BEV-SAEV

Type	PT	CdA (m²)	Glider Mass (kg)	Aux. Power (kW)	Weight (kg)
LP Sensors	BEV	.825	658	0.325	1768
HP Sensors	BEV	0.830	670.4	0.4897	1780.4

Chevy Bolt	Base	SAEV (LP Sensors)	Change (%)	SAEV (HP Sensors)	Change (%)
City Eff. (kWh/mi)	0.231	0.237	-2.6%	0.251	-8.7%
Highway Eff. (kWh/mi)	0.275	0.278	-1.1%	0.285	-3.6%
Combined Eff. (kWh/mi)	0.251	0.256	**-2.0%**	**0.266**	**-6.0%**
Range	**237**	**232**	**-2.1%**	**223**	**-5.8%**

Figure 31: BEV Medium-SAEV Prototype Performance Characteristics

As shown with other prototype vehicles, the corresponding sensor-level analysis is shown below.

BEV-SAEV

BEV Medium-SAEV	Base	SAEV (+"Large Drag")	Change (%)	SAEV (+"Large Mass")	Change (%)	SAEV (+"Large Pwr")	Change (%)
City Eff. (kWh/mi)	0.231	0.2315	-0.2%	0.2327	-0.7%	0.2487	-7.7%
Highway Eff. (kWh/mi)	0.275	0.2765	-0.5%	0.2766	-0.6%	0.2826	-2.8%
Combined Eff. (kWh/mi)	**0.251**	0.2517	**-0.3%**	**0.2524**	**-0.6%**	**0.2639**	**-5.1%**
Range	**237**	**235.9**	**-0.5%**	**235.3**	**-0.7%**	**224.4**	**-5.3%**

Figure 32: BEV Medium-SAEV Sensor-Level Energy Impacts

Adding the same sensor configurations to the FCEV Medium-SAEV yields the results shown in Figure 33, and for sensor-level impacts in Figure 34.

FCEV-SAV

Type	PT	Tank (kg)	Range (Miles)	Weight (kg)
LP Sensors	FCEV	5	307	1940
HP Sensors	FCEV	5	298	1952

Toyota Mirai	Base	SAEV (LP Sensors)	Change (%)	SAEV (HP Sensors)	Change (%)
City MPGGE	68.6	66.8	-2.6%	64.6	-5.8%
Highway MPGGE	65.1	64.6	-0.8%	63.4	-2.6%
Combined MPGGE	**67.0**	65.8	**-1.8%**	**64.1**	**-4.3%**
Range	**312**	**307**	**-1.6%**	**298**	**-4.5%**

Figure 33: FCEV Medium-SAEV Prototype Performance Characteristics

FCEV Medium-SAEV	Base	SAEV (+"Large Drag")	Change (%)	SAEV (+"Large Mass")	Change (%)	SAEV (+"Large Pwr")	Change (%)
City MPGGE	68.6	68.5	-0.1%	68.3	-0.4%	65.0	-5.2%
Highway MPGGE	65.1	64.8	-0.5%	65.0	-0.2%	63.9	-1.8%
Combined MPGGE	**67.0**	66.8	**-0.3%**	**66.7**	**-0.4%**	**64.5**	**-3.7%**
Range	**312**	**311.1**	**-0.3%**	**310.9**	**-0.4%**	**300.4**	**-3.7%**

Figure 34: FCEV Medium-SAEV Sensor-Level Energy Impacts

4.3.1.4 Large-SAEV Designs

The final SAEV prototype to explore in this work is the Large-SAEV, which is based on the 2017 Chrysler Pacifica PHEV minivan. Just as was done with the Elio, the Pacifica will be first established as a baseline in FASTSim and then converted from its regular PHEV powertrain to BEV and FCEV. The resulting baseline FASTSim vehicle results are shown below.

Type	PT	CdA (m²)	Glider Mass (kg)	Aux. Power (kW)	Weight (kg)
Base	ICV (3.6L)	0.92	1352	0.7	1964

FASTSim Results

	Actual	FASTSim	Error (%)
City MPG	19	19.8	4.2%
Highway MPG	28	26.7	-4.6%
Combined MPG	**22.2**	**22.4**	0.9%

Figure 35: Large-SAEV Base Vehicle, Chrysler Pacifica PHEV, Parameters and FASTSim Results

While the error of the combined MPG is a bit higher than the result for the Elio vehicle, the FASTSim result will be used as the baseline for further comparison. From that, the changes from adding the low and high-profile sensors to the Large-SAEV can be observed. Refer to Figure 36 below for the corresponding energy impact results.

SAV

Type	PT	CdA (m²)	Glider Mass (kg)	Aux. Power (kW)	Weight (kg)
LP Sensors	ICV (3.6L)	0.92	1362	0.775	1974
HP Sensors	ICV (3.6L)	0.93	1372.4	0.94	1984.4

	Base	ICV SAV (LP Sensors)	Change (%)	ICV SAV (HP Sensors)	Change (%)
City MPG	19.8	19.5	-1.5%	18.8	-5.1%
Highway MPG	26.7	26.5	-0.7%	26.1	-2.2%
Combined MPG	**22.4**	**22.1**	**-1.2%**	**21.5**	**-4.0%**
Range	**421**	**417**	**-1.0%**	**405.0**	**-3.8%**

Figure 36: Pacifica PHEV-SAV Concept, Relative Effects of Low and High-Profile Sensors on Performance

For consistency with the previous ICV shown, the sensor-level energy impacts are shown for the Pacifica ICV as well below.

SAV

ICV Pacifica	Base	SAV (+"Large Drag")	Change (%)	SAV (+"Large Mass")	Change (%)	SAV (+"Large Pwr")	Change (%)
City MPG	19.8	19.7	-0.5%	19.7	-0.5%	18.9	-4.5%
Highway MPG	26.7	26.6	-0.4%	26.6	-0.4%	26.2	-1.9%
Combined MPG	**22.4**	**22.3**	**-0.5%**	**22.3**	**-0.5%**	**21.6**	**-3.6%**
Range	**421**	**421**	**0.0%**	**420.0**	**-0.2%**	**407.0**	**-3.3%**

Figure 37: ICV Pacifica Sensor-Level Energy Impacts

The BEV Large-SAEV prototype also borrows the Tesla Model S P100 powertrain for testing purposes. Rather than using just one-quarter of the battery modules, however, this prototype is assumed to fit the entire battery pack and associated equipment within its footprint, which is comparable to the Tesla Model S. Please refer to Figure 38 for an illustration.

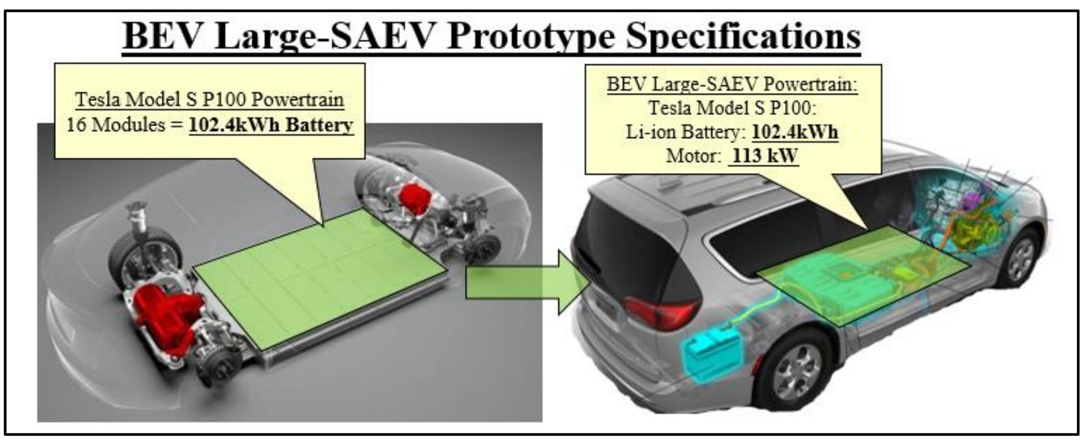


Figure 38: BEV Large-SAEV Prototype Specifications

Note that the physical dimensions of the Pacifica are large enough to seat the Tesla powertrain batteries without stacking batteries on one another. However, if necessary, the in-cabin storage capability of the Pacifica would be able to accommodate more cells or equipment if necessary. For example, the *Stow 'n Go®* seating and storage area of the standard Pacifica is used in the PHEV model to house the lithium-ion PHEV batteries. The motor and ECU would be positioned in the same location, the engine bay, as they are positioned in the Pacifica PHEV. The difference being, the size of the electric motor would be increased to compensate for then providing all motive force for the vehicle. The size of such electric powertrain components is assumed to be comparable with the size of the internal combustion engine and associated powertrain components being replaced, such that all BEV components can fit into the existing footprint of the vehicle.

In terms of performance, the BEV Large-SAEV is still able to achieve a relatively reasonable range for both the low and high-profile sensor installations, as seen below.

BEV-SAEV

Type	PT	Battery (kWh)	Range (Miles)	Weight (kg)
LP Sensors	113kW	102.4	274	3072
HP Sensors	113kW	102.4	266	3082.4

Chrysler Pacifica	Base	SAEV (LP Sensors)	Change (%)	SAEV (HP Sensors)	Change (%)
City Eff. (kWh/mi)	0.303	0.309	-2.0%	0.322	-6.3%
Highway Eff. (kWh/mi)	0.326	0.328	-0.6%	0.335	-2.8%
Combined Eff. (kWh/mi)	0.313	0.317	**-1.4%**	0.328	**-4.7%**
Range	**278**	**274**	**-1.4%**	**266**	**-4.3%**

Figure 39: BEV Large-SAEV Prototype Performance Characteristics

Corresponding sensor-level impacts for the BEV Large-SAEV are shown below.

BEV Large-SAEV	Base	SAEV (+"Large Drag")	Change (%)	SAEV (+"Large Mass")	Change (%)	SAEV (+"Large Pwr")	Change (%)
City Eff. (kWh/mi)	0.303	0.303	0.0%	0.304	-0.3%	0.320	-5.6%
Highway Eff. (kWh/mi)	0.326	0.327	-0.3%	0.326	0.0%	0.333	-2.1%
Combined Eff. (kWh/mi)	0.313	0.313	-0.1%	0.314	-0.2%	0.326	-4.1%
Range	278	277	-0.4%	277.0	-0.4%	267.0	-4.0%

Figure 40: BEV Large-SAEV Sensor-Level Energy Impacts

The Toyota Mirai provides the basic powertrain components for the FCEV Large-SAEV, just as was the case for the FCEV Micro-SAEV. The components are sized to meet the performance characteristics of the base Pacifica PHEV from which it is modelled after. Please refer to for Figure 41 for a clearer illustration of these components and their characteristics.

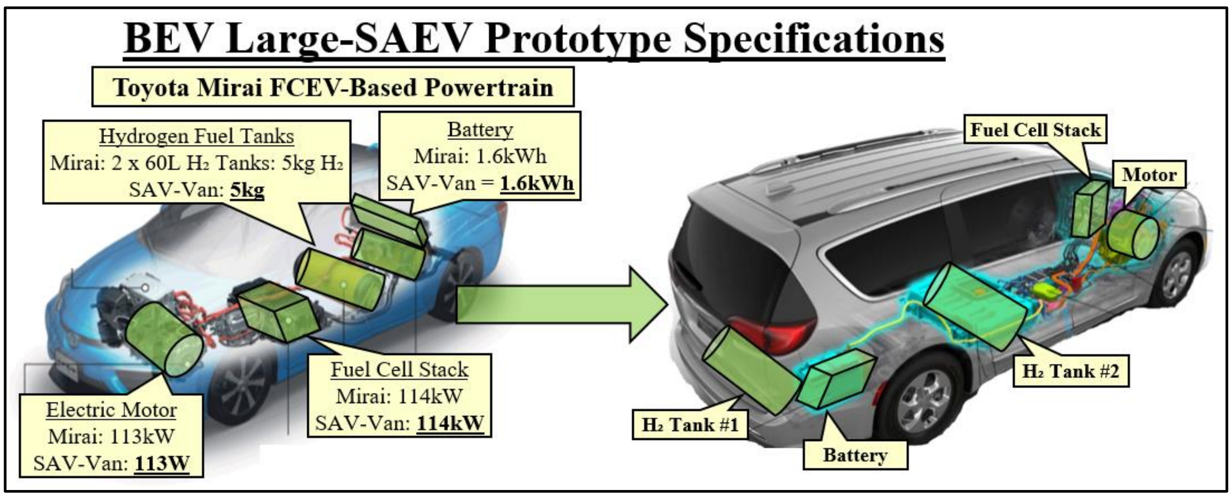


Figure 41: FCEV Large-SAEV Prototype Specifications

Like the Mirai and other commercially available FCEVs, this prototype FCEV would use two hydrogen tanks to aide with the efficient use of space. It is assumed that the FCEV components and equipment would be able to fit in the vehicle such that the passenger room would still be able to accommodate eight people. The performance of this vehicle is described in Figure 42 below.

FCEV-SAEV

Type	PT	Tank (kg)	Range (Miles)	Weight (kg)
LP Sensors	113kW	5	288	2120
HP Sensors	113kW	5	280	2132.4

Chrysler Pacifica	Base	SAEV (LP Sensors)	Change (%)	SAEV (HP Sensors)	Change (%)
City MPGGE	62.7	61.6	-1.8%	59.5	-5.1%
Highway MPGGE	62.4	62.0	-0.6%	60.9	-2.4%
Combined MPGGE	62.6	61.8	**-1.3%**	60.1	**-3.9%**
Range	**291**	**288**	**-1.0%**	**280**	**-3.8%**

Figure 42: FCEV Large-SAEV Prototype Performance Characteristics

As with the Micro-SAEV prototypes, the Large-SAEV prototypes reflect the general FCEV advantage of improved range performance. This prototype performs relatively well when compared to other FCEVs of its general size. For example, the 2019 Hyundai Nexo achieves a combined MPGGE of 57, which is nearly the same performance as both FCEV Large-SAEV prototypes tested [156].

The individual sensor impacts associated with the FCEV large-SAEV are shown below.

FCEV-SAEV

FCEV Large-SAEV	Base	SAEV (+"Large Drag")	Change (%)	SAEV (+"Large Mass")	Change (%)	SAEV (+"Large Pwr")	Change (%)
City MPGGE	62.7	62.6	-0.2%	62.5	-0.3%	59.700	-4.8%
Highway MPGGE	62.4	62.2	-0.3%	62.2	-0.3%	61.200	-1.9%
Combined MPGGE	62.6	62.4	**-0.2%**	62.4	**-0.3%**	60.4	**-3.5%**
Range	**291**	**291**	**0.0%**	**291.0**	**0.0%**	**281.0**	**-3.4%**

Figure 43: FCEV Large-SAEV Sensor-Level Energy Impacts

4.3.2 V2V and V2I Control Implementation

The prototype SAEVs designed and measured for sensor integration efficiency impacts are now to be aided by connected vehicle (i.e., V2V and V2I) controls. These controls will enhance the driving dynamics of each SAEV via eco-driving in a city scenario and platooning in a highway scenario. FETCH is implemented in this section to measure the changes in efficiency using the standard drive cycles used to evaluate each new domestically sold vehicle. The domestic test procedures for measuring energy efficiency (e.g., fuel economy, or MPG) is to test a vehicle in a city and highway scenario, and then to weight the efficiency measurement slightly in favor of the city measurement. To make results as comparable as possible, FETCH is employed to simulate prototype SAEVs in scenarios which reflect these city and highway test procedures, as enhanced by the addition of V2V and V2I.

4.3.2.1 Prototype SAEV Testing for City Drive Cycle

The city drive cycle used for the following scenarios is the Urban Dynamometer Driving Schedule (UDDS), developed by the US EPA. This test simulates a city driving pattern, with numerous accelerations and decelerations, as seen an illustration of the drive cycle in Figure 44 below [157].

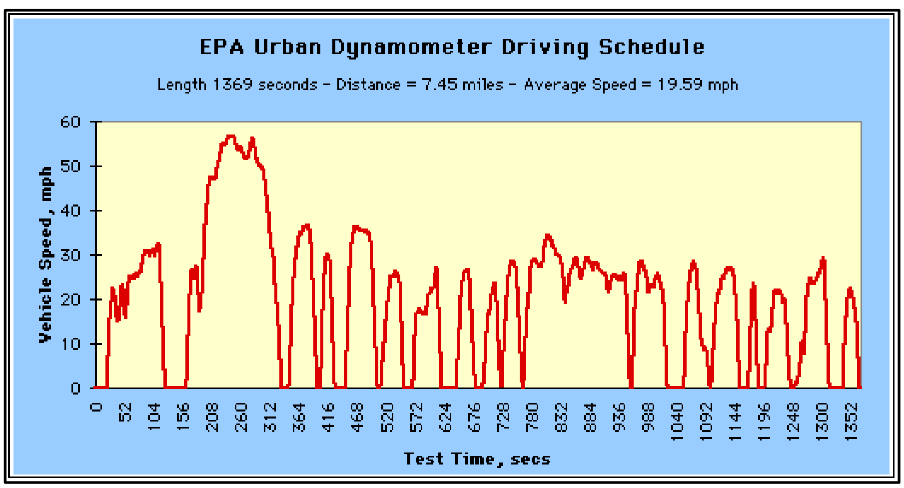


Figure 44: Urban Dynamometer Driving Schedule (UDDS) Graph, (Source: US EPA)

The *City* component of FASTSim results uses this drive cycle to measure the corresponding efficiency. But what if the vehicle tested in this procedure was a connected vehicle? Rather than accelerating and decelerating at so many instances, it would be possible for that connected SAEV to receive an advanced warning, or advice, from nearby vehicles or infrastructure of an upcoming hazard, red light, change in speed, or so on. Considering that the UDDS represents a city scenario, it is assumed for the following scenarios that the stops and starts are the result of stoplights. A V2I-enhanced city scenario, which was previously found to elicit amongst the highest potential for fuel economy improvement, was implemented as following in Figure 45.

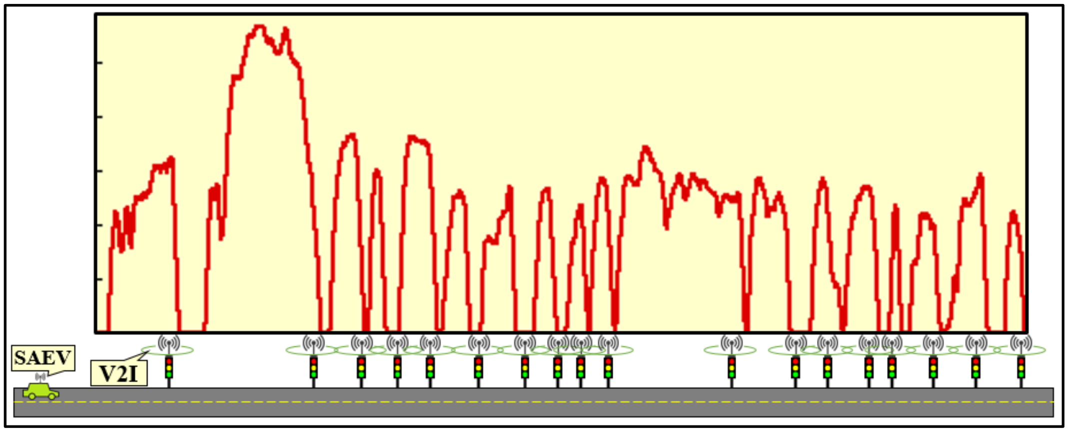


Figure 45: UDDS V2I Schematic

The figure above shows that just prior to a slowdown, a V2I-enabled traffic light will warn the upcoming SAEV to slow down ahead of time, thus preventing unnecessary acceleration and deceleration. Several V2I parameters were explored for their efficacy in improving energy efficiency including beacon range, V2I control (i.e., deceleration profile), and communication protocol (i.e., 802.11p-based Direct Short-Range Communications (DSRC) vs 4G-LTE).

The goal of using V2I controls in this scenario is to reduce the wasteful stop-and-go behavior of the standard UDDS driving profile. When the V2I-enabled (i.e., connected) SAEV prototype is in range of the V2I-enabled traffic light, the light will send a message to that vehicle with a deceleration command. After the SAEV completes this V2I-enhanced the UDDS cycle, the new resulting driving profile is considered representative of the more efficient driving behavior of the connected vehicle, for the messaging range used. This DSRC-based V2I scenario was chosen in favor over the tested 4G-LTE scenario due to latency concerns recently explored by researchers in partnership with the California Department of Transportation [158], though future research efforts could explore the efficacy of similar networks with potentially lower latency (e.g., 5G networks). The connected vehicle drive cycles are shown below in Figure 46 through Figure 48, each with a green V2I-enabled drive cycle superimposed onto a graph of the standard UDDS drive cycle.

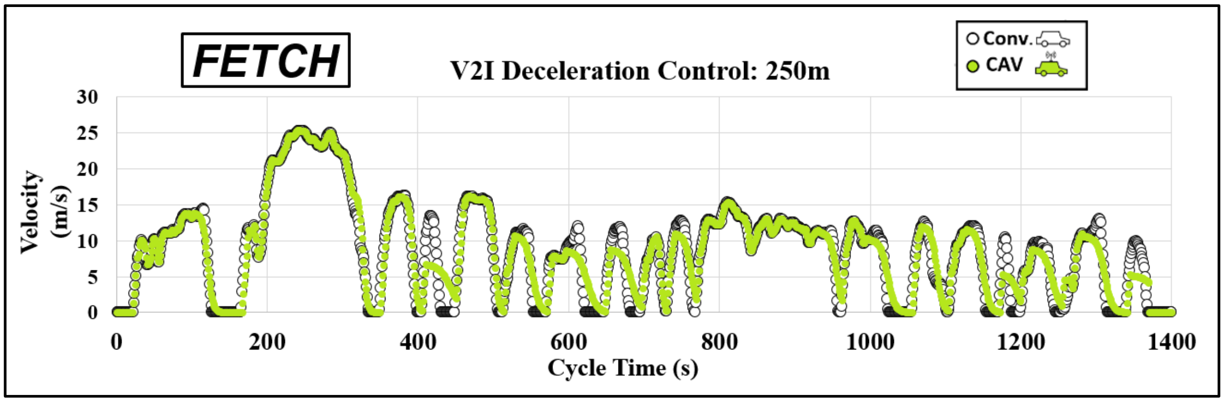


Figure 46: V2I Deceleration Control, 250m Range

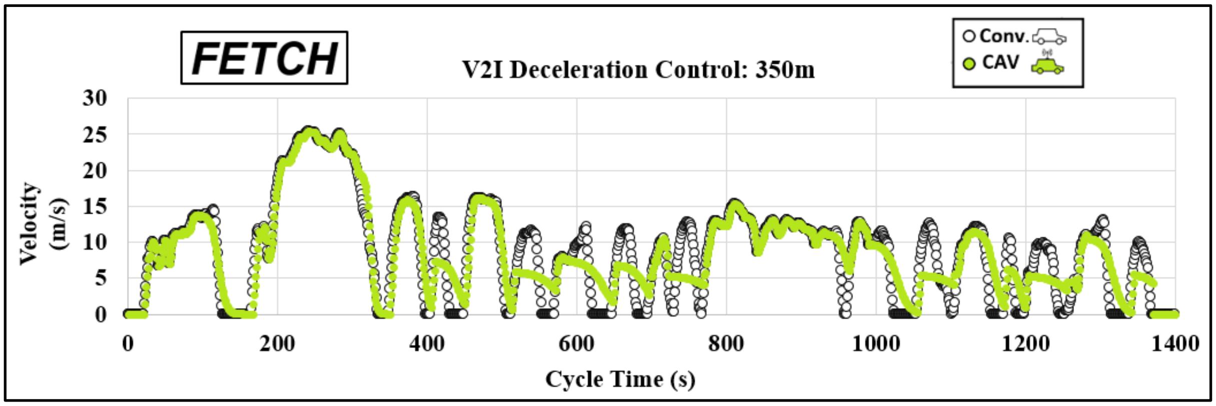


Figure 47: V2I Deceleration Control, 350m Range

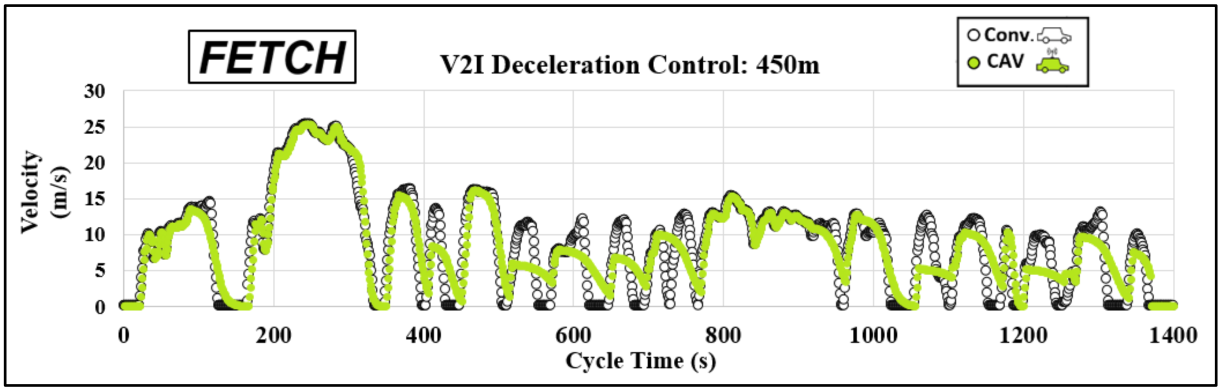


Figure 48: V2I Deceleration Control, 450m Range

Note that when a connected vehicle receives the command to decelerate in advance, it is able to prevent the degree of acceleration that would otherwise be normal for the UDDS drive cycle. While the V2I range progressively improves this performance, the returns for energy savings are diminishing as the results for 350m and 450m appear to be similar. The V2I controls shared in this work were found to elicit the greatest energy efficiency improvement when compared with other deceleration profiles using FETCH. These range-varying V2I-enabled drive cycles will serve as inputs into FASTSim to measure the energy impacts for city driving scenarios.

4.3.2.2 Prototype SAEV Testing for Highway Drive Cycle

Highway driving scenarios will largely benefit from the aerodynamic drag reductions of V2V-enabled platooning, as the driving profile is already relatively smooth, and the relative importance of drag reduction is high at higher speeds. Just as the city-driving scenario used the standard representative UDDS drive cycle, the highway scenario will use the standard representative highway drive-cycle for calculating MPG, which is referred to as the Highway Fuel Economy Driving Schedule (HWFET) and is shown below [157].

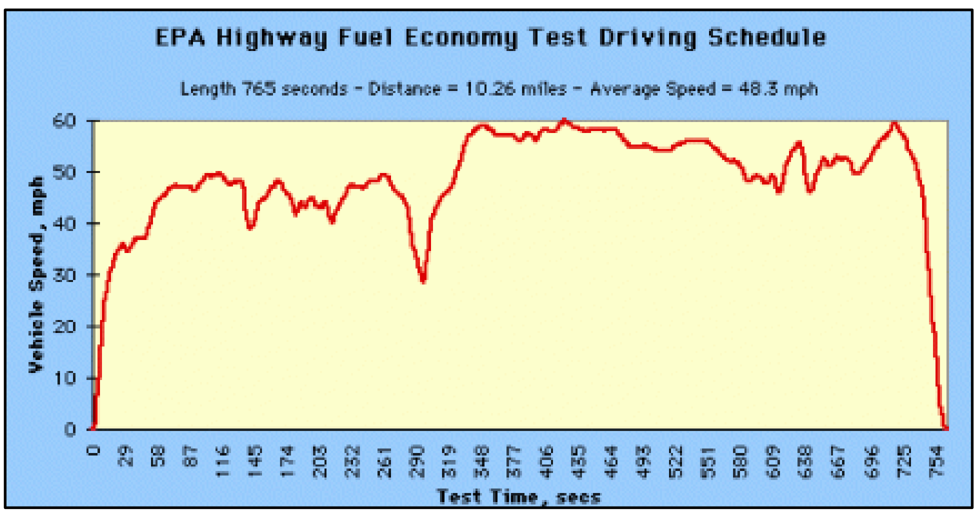


Figure 49: Highway Fuel Economy Driving Schedule (HWFET) Graph, Source: US EPA

While eco-driving would be less suitable to smooth out excessive accelerations and decelerations for such highway scenario, connected vehicle technology can still allow for significant efficiency improvements via platooning-enabled aerodynamic drag reduction. For example, Romberg et al. used a wind tunnel and scale models of 1970's-era race cars, which resemble boxy sedans, to measure the drag reduced for two vehicles involved in various drafting (i.e., platooning for racing purposes) configurations [159]. When the trailing vehicle was one car-length behind the leading vehicle, the researchers measured a 30% reduction in drag force, and a combined reduction of 27% in drag force for a following length of one-half of a car-length. Zabat et al. also used a used a wind tunnel and scale models, measuring a maximum mean drag coefficient reduction of 38%, for a platoon of 4 minivans following at a half of a car-length [160]. For the same following length, the researchers also measured mean drag coefficient reductions of 25% and 32% for two-vehicle and three-vehicle platoons, respectively. These results were again confirmed by later testing from the same group [161]. Schito et al. again investigated the effect of platooning on drag coefficient for various vehicle types in various platooning configurations, while also using Computational Fluid Design (CFD) techniques to confirm results [162]. Homogeneous and mixed fleets of compact cars, sedans, vans, and trucks were all investigated for their potential to benefit from platooning and mean drag coefficient reductions measured from 20% to 60%. Such platooning studies have spanned decades and continue to investigate potential innovations. For example, a recent study by Le Good et al. tested the drag coefficient reduction possible through the so-called morphing of exterior body panels, such that when platooning, vehicles would be able to adjust their geometry to enable the greatest fleet benefit possible [163].

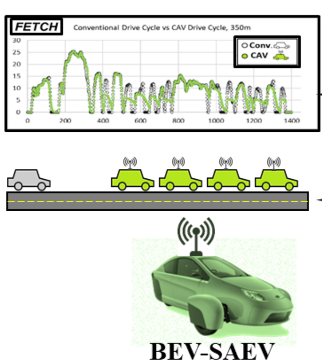
The selection of academic studies discussed above share how the implications of platooning largely depend on the number of vehicles in the platoon, the vehicle geometry, and following distance, and speed. Just as FETCH is used to evaluate several V2I-enhanced city-driving scenarios, several platooning-enhanced highway-driving scenarios will be evaluated as well. Whereas the range of V2I communications was spanned to evaluate city-driving efficiency improvements, the span of potential drag coefficient reduction will be varied to encompass the potential efficiency improvements for prototype SAEVs traveling on the highway. For the purposes of this work, the drag coefficient reductions are 10%, 20%, and 40%. While the maximum drag coefficient reductions can be greater individual following vehicles, the maximum value of 40% for this span was chosen to help represent a feasible upper limit for a hypothetical fleet average.

4.3.3 Prototype SAEV Testing Results

Prototype SAEVs are now designed, their sensor configurations and their potential efficiency impacts are explored, and the corresponding city and highway driving scenarios are defined. Now, vehicle-centric energy impacts can be measured for each prototype SAEV using FETCH.

4.3.3.1 BEV Micro-SAEV Vehicle Centric Energy Impacts

The results of the BEV Micro-SAEV vehicle energy impacts are shown immediately below:

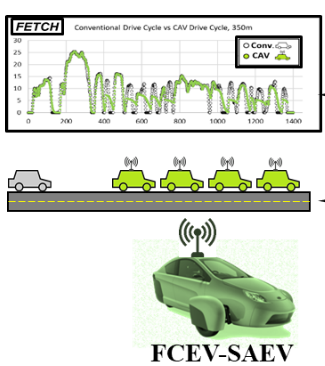


	Base	Change (%)	BEV-SAEV (Small Sensors)	Change (%)	BEV-SAEV (Large Sensors)	Change (%)
Base City Eff. (kWh/mi)	0.180	-	0.186	-	0.199	-
City Eff., V2I: 250m	0.163	9.4%	0.169	9.1%	0.183	8.0%
City Eff., V2I: 350m	0.151	16.1%	0.157	15.5%	0.171	14.1%
City Eff., V2I: 450m	0.148	17.8%	0.154	17.1%	0.167	16.1%
Base Highway Eff. (kWh/mi)	0.150	-	0.152	-	0.159	-
Highway Eff., V2V: -10% Drag	0.144	4.0%	0.146	3.9%	0.153	3.8%
Highway Eff., V2V: -20% Drag	0.138	8.0%	0.140	7.9%	0.147	7.5%
Highway Eff., V2V: -40% Drag	0.125	16.7%	0.128	15.8%	0.134	15.7%
Combined Eff., Low Estimate	**0.154**	**7.9%**	**0.158**	**7.7%**	**0.168**	**7.1%**
Combined Eff., High Estimate	**0.137**	**18.2%**	**0.141**	**17.5%**	**0.150**	**16.9%**
Range, Low Estimate	**149**	**7.9%**	**145**	**7.7%**	**135**	**7.1%**
Range, High Estimate	**163**	**18.2%**	**159**	**17.5%**	**147**	**16.9%**

Figure 50: BEV Micro-SAEV Vehicle-Centric Energy Impacts

Note that the energy impact of the Small Sensor configuration *immediately* makes up for the added weight, drag, and power of the sensors within the very first City and Highway scenario. Yet, the weight, drag, and power draw associated with the *Large* Sensor concept requires a 350m range V2I beacon to make for eco-driving savings beyond the energy costs of those sensors. The same impact is seen in the highway scenario, where the base efficiency is 0.150 kWh/mi and the 10% drag reduction does not provide enough energy savings to overcome the large sensor installation costs as well. Overall, the vehicle-centric energy impacts are relatively significant. Note, however, that the percent improvement of sensor integration *decreases* as the associated sensor-loads increase (i.e., the overall 7.9% and 18.2% of the base-case decrease to 7.1% and 16.9% for the Large Sensor integration strategy). This is likely due to increases in power consumption, which unlike weight or drag, cannot be affected by the benefits of eco-driving and platooning. This trend is relatively insignificant, approximately a 1% difference, though it underscores the importance of reducing SAEV-sensor power consumption. The following figures show the energy impact results of the remaining prototypes considered in this work.

4.3.3.2 FCEV Micro-SAEV Vehicle Centric Energy Impacts

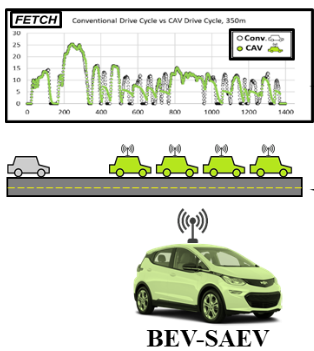


	Base	Change (%)	FCEV-SAEV (Small Sensors)	Change (%)	FCEV-SAEV (Large Sensors)	Change (%)
Base City MPGGE	78.8	-	77.4	-	73.8	-
City MPGGE, V2I: 250m	88.0	11.7%	86.6	11.9%	83.5	13.1%
City MPGGE, V2I: 350m	92.7	17.6%	91.1	17.7%	87.5	18.6%
City MPGGE, V2I: 450m	95.3	20.9%	93.7	21.1%	90.0	22.0%
Base Highway (HW) MPGGE	102.9	-	101.7	0.0%	98.8	-
HW MPGGE, V2V: -10% Drag	106.3	3.3%	104.9	3.1%	101.8	3.0%
HW MPGGE, V2V: -20% Drag	109.7	6.6%	108.4	6.6%	104.9	6.2%
HW MPGGE, V2V: -40% Drag	118.1	14.8%	116.3	14.4%	112.6	14.0%
Comb. MPGGE, Low Estimate	**95.4**	**8.3%**	**94.0**	**8.4%**	**90.8**	**9.1%**
Comb. MPGGE, High Estimate	**104.4**	**18.5%**	**102.7**	**18.4%**	**98.9**	**18.8%**
Range, Low Estimate	**238**	**8.3%**	**235**	**8.4%**	**227**	**9.1%**
Range, High Estimate	**261**	**18.5%**	**257**	**18.4%**	**247**	**18.8%**

Figure 51: FCEV Micro-SAEV Vehicle-Centric Energy Impacts

While the overall energy impact trends are similar between the BEV and FCEV-Micro SAEV prototypes, a noteworthy difference exists between the degree to which eco-driving and platooning benefit the Large Sensor configurations of these vehicles. Specifically, the FCEV-powertrain Micro-SAEV stands to benefit more than the BEV in the city-driving scenarios. This is possibly because of the significant difference in weight characteristic of the BEV-powertrain relative the weight of the FCEV-powertrain. Each powertrain is scaled similarly, and has similar efficiencies, though the BEV Micro-SAEV overall weighs about 200 kg more than the FCEV Micro-SAEV. This additional weight would negatively affect the city-driving scenario efficiency more than the highway scenario, as has been found by Argonne National Laboratory researchers [164].

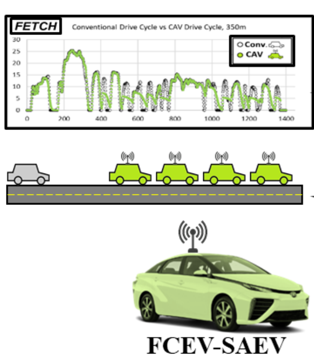
4.3.3.3 BEV Medium-SAEV Vehicle Centric Energy Impacts



	Base	Change (%)	BEV-SAEV (Small Sensors)	Change (%)	BEV-SAEV (Large Sensors)	Change (%)
Base City Eff. (kWh/mi)	0.231	-	0.237	-	0.251	-
City Eff., V2I: 250m	0.216	6.5%	0.222	6.3%	0.235	6.4%
City Eff., V2I: 350m	0.205	11.3%	0.211	11.0%	0.225	10.4%
City Eff., V2I: 450m	0.203	12.1%	0.209	11.8%	0.223	11.2%
Base Highway Eff. (kWh/mi)	0.275	-	0.278	-	0.285	-
Highway Eff., V2V: -10% Drag	0.259	5.8%	0.262	5.8%	0.269	5.6%
Highway Eff., V2V: -20% Drag	0.243	11.6%	0.246	11.5%	0.253	11.2%
Highway Eff., V2V: -40% Drag	0.211	23.3%	0.214	23.0%	0.220	22.8%
Combined Eff., Low Estimate	**0.233**	**7.0%**	**0.238**	**6.9%**	**0.249**	**6.3%**
Combined Eff., High Estimate	**0.207**	**17.7%**	**0.211**	**17.5%**	**0.222**	**16.7%**
Range, Low Estimate	**254**	**7.0%**	**248**	**6.9%**	**237**	**6.3%**
Range, High Estimate	**279**	**17.7%**	**273**	**17.5%**	**261**	**16.7%**

Figure 52: BEV Medium-SAEV Vehicle-Centric Energy Impacts

4.3.3.4 FCEV Medium-SAEV Vehicle Centric Energy Impacts

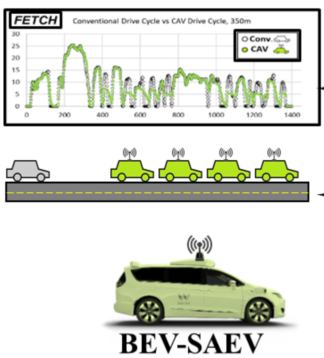


	Base	Change (%)	FCEV-SAEV (Small Sensors)	Change (%)	FCEV-SAEV (Large Sensors)	Change (%)
Base City MPGGE	68.6	-	66.8	-	64.6	-
City MPGGE, V2I: 250m	73.4	7.0%	71.9	7.6%	69.2	7.1%
City MPGGE, V2I: 350m	75.2	9.6%	73.6	10.2%	70.6	9.3%
City MPGGE, V2I: 450m	76.0	10.8%	74.5	11.5%	71.4	10.5%
Base Highway (HW) MPGGE	65.1	-	64.6	-	63.4	-
HW MPGGE, V2V: -10% Drag	68.0	4.5%	67.5	4.5%	66.2	4.4%
HW MPGGE, V2V: -20% Drag	71.2	9.4%	70.7	9.4%	69.3	9.3%
HW MPGGE, V2V: -40% Drag	78.7	20.9%	78.0	20.7%	76.3	20.3%
Comb. MPGGE, Low Estimate	**70.9**	**5.8%**	**69.9**	**6.2%**	**67.8**	**5.8%**
Comb. MPGGE, High Estimate	**77.2**	**15.2%**	**76.0**	**15.6%**	**73.5**	**14.7%**
Range, Low Estimate	**330**	**5.8%**	**326**	**6.2%**	**315**	**5.8%**
Range, High Estimate	**359**	**15.2%**	**355**	**15.6%**	**342**	**14.7%**

Figure 53: FCEV Medium-SAEV Vehicle-Centric Energy Impacts

Note for the Medium-SAEV prototypes, that the trends appear to be reversed for which powertrain stands to benefit the most from city-driving scenarios. However, just as was the case for the Micro-SAEVs, weight is a primary factor for city-driving efficiency. In this case, the FCEV Medium SAEV weighs more than the BEV-SAEV. The difference in weight is relatively small, and there is a correspondingly smaller difference in city-driving efficiency.

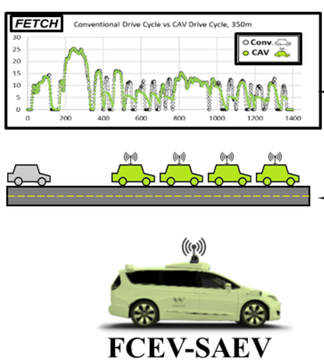
<u>4.3.3.5 BEV Large-SAEV Vehicle Centric Energy Impacts</u>



	Base	Change (%)	BEV-SAEV (Small Sensors)	Change (%)	BEV-SAEV (Large Sensors)	Change (%)
Base City Eff. (kWh/mi)	0.303	-	0.309	-	0.322	-
City Eff., V2I: 250m	0.284	-6.3%	0.290	-6.1%	0.303	-5.9%
City Eff., V2I: 350m	0.269	-11.2%	0.275	-11.0%	0.288	-10.6%
City Eff., V2I: 450m	0.267	-11.9%	0.273	-11.7%	0.287	-10.9%
Base Highway Eff. (kWh/mi)	0.326	-	0.328	-	0.335	-
Highway Eff., V2V: -10% Drag	0.308	-5.5%	0.311	-5.2%	0.317	-5.4%
Highway Eff., V2V: -20% Drag	0.291	-10.7%	0.293	-10.7%	0.299	-10.7%
Highway Eff., V2V: -40% Drag	0.256	-21.5%	0.258	-21.3%	0.264	-21.2%
Combined Eff., Low Estimate	**0.294**	**5.9%**	**0.299**	**5.7%**	**0.309**	**5.7%**
Combined Eff., High Estimate	**0.262**	**16.3%**	**0.266**	**16.1%**	**0.276**	**15.7%**
Range, Low Estimate	**295**	**5.9%**	**290**	**5.7%**	**281**	**5.7%**
Range, High Estimate	**323**	**16.3%**	**318**	**16.1%**	**308**	**15.7%**

Figure 54: BEV Large-SAEV Vehicle-Centric Energy Impacts

<u>4.3.3.6 FCEV Large-SAEV Vehicle Centric Energy Impacts</u>



	Base	Change (%)	FCEV-SAEV (Small Sensors)	Change (%)	FCEV-SAEV (Large Sensors)	Change (%)
Base City MPGGE	62.7	-	61.6	-	59.5	-
City MPGGE, V2I: 250m	68.1	8.6%	66.9	8.6%	64.6	8.6%
City MPGGE, V2I: 350m	70.2	12.0%	68.9	11.9%	66.3	11.4%
City MPGGE, V2I: 450m	70.9	13.1%	69.7	13.1%	67.0	12.6%
Base Highway (HW) MPGGE	62.4	-	62.0	-	60.9	-
HW MPGGE, V2V: -10% Drag	65.5	5.0%	65.1	5.0%	63.9	4.9%
HW MPGGE, V2V: -20% Drag	69.0	10.6%	68.5	10.5%	67.2	10.3%
HW MPGGE, V2V: -40% Drag	76.9	23.2%	76.4	23.2%	74.8	22.8%
Comb. MPGGE, Low Estimate	**66.9**	**6.9%**	**66.1**	**7.0%**	**64.3**	**6.9%**
Comb. MPGGE, High Estimate	**73.5**	**17.4%**	**72.6**	**17.5%**	**70.3**	**16.9%**
Range, Low Estimate	**311**	**6.9%**	**308**	**7.0%**	**299**	**6.9%**
Range, High Estimate	**342**	**17.4%**	**338**	**17.5%**	**327**	**16.9%**

Figure 55: FCEV Medium-SAEV Vehicle-Centric Energy Impacts

4.4 Vehicle-Centric Energy Impacts Discussion

The preceding results measure the vehicle-centric energy impacts of six difference SAEV prototypes and demonstrate the usefulness of the FETCH Tool to evaluate various possible SAEV designs and control strategies. Such results will serve as the inputs for the remaining sections of this work and are summarized in the figure below.

	Base Efficiency	Efficiency, Low Estimate	Efficiency, High Estimate	Base Range	Range, Low Estimate	Range, High Estimate
 **BEV-SAEV**	0.167	0.168 **(-0.6%)**	0.141 **(+15.6%)**	138	134	158
 **FCEV-SAEV**	88.1	91 **(+3.3%)**	103 **(+16.9%)**	220	227	257
 **BEV-SAEV**	0.251	0.249 **(+0.8%)**	0.211 **(+15.9%)**	237	237	272
 **FCEV-SAEV**	67.0	68 **(+1.5%)**	76 **(+13.4%)**	312	315	355
 **BEV-SAEV**	0.313	0.309 **(+1.3%)**	0.266 **(+15.0%)**	278	281	318
 **FCEV-SAEV**	62.6	64 **(+2.2%)**	73 **(+16.6%)**	291	299	338

Figure 56: Vehicle-Centric Energy Impacts Summary

While the SAEV prototype designs and associated sensor configurations presented represent a reasonable approximation of future SAEVs at this time, there will certainly continue to be innovations in vehicle design, processing power, powertrain efficiency, and so on. Therefore, the contribution of this work is not the results themselves, but rather the FETCH Tool and associated research framework. Such tools provide researchers with the ability to compare critical aspects of future vehicles as they continue to evolve for years to come.

5. Measure Fleet-Centric Energy Impacts of SAEVs

The study of vehicle-centric energy impacts requires a very detailed look into the technical characteristics of individual SAEVs, and the fleet-centric energy impact assessment requires a similarly detailed investigation into the broader perspective of how these SAEVs will be deployed throughout California. The energy that the overall SAEV deployment will consume depends largely on VMT (and therefore the location and size of SAEV stations) and vehicular energy efficiency. This section measures such fleet attributes such that the vehicle and fleet-centric impacts can combine for an overall energy impact for the final grid and environmental modeling stages. Firstly, this chapter will detail 2010 and 2050 station siting scenarios based on a novel "Nice-SAEV" neighborhood carsharing and ridesharing program. Next, SAEV fleets will be defined based on vehicle range, powertrain, and the demands of participating neighborhoods for the projected 2050 Nice-SAEV scenario. Lastly, this section ends with a brief summary and conclusions to help transition into the final sections of the dissertation.

5.1 The "Nice-SAEV" Car and Ridesharing Program

Imagine a future scenario where the state of California would like to reduce individual's use of conventional vehicles for short-distance neighborhood trips, all using state-owned and operated SAEVs. Such trips might include the drive to a grocery store that is really within a walking distance, but often driven to for comfort and convenience. Or, where despite the local school being nearby, a parent chooses to drive and pick up their children rather than walk. Such are the trips that the state of California would like to reduce, and the recent advent of the SAEV means that a transition from the conventionally-driven ICVs, and to the robotically-driven EVs can unlock previously impossible ways of improving transportation sector efficiency.

Californians will be able to conveniently order a ride, either private or pooled, with their smartphone or other connected device to safely and efficiently arrive at their destination.

The California Department of Transportation (Caltrans) currently owns over 350 Park-and-Ride parking lots for commuters to interface with the public transit [165]. For the Nice-SAEV program, state agencies will choose to work with Caltrans to re-allocate some parking spaces for use with Nice-SAEV program to serve as automated charging and fueling spaces. If necessary for areas of high demand, Caltrans agrees to invest discretionary funds into building parking structures on land of current Park-and-Ride locations to accommodate the valuable Nice-SAEV program. After a brief discussion of methods, the first planning steps involved are the selection of which Park-and-Ride lots will serve as Nice-SAEV Stations or, more simply, *SAEV Stations*.

5.1.1 Nice-SAEV Passenger Travel Data

To model the impacts of the Nice-SAEV program, one must measure the difference between how trips would be served with the program and how they would be served under conventional circumstances. The trip properties, such as mode choice, trip purpose, occupancy, and spatial and temporal distribution, must all be understood for California. The California Department of Transportation (Caltrans) Short Distance Personal Travel Model (SDPTM) component of the California Statewide Travel Demand Model (CSTDM) is used for this purpose [166],[167]. This dataset consists of millions of simulated trips representing every trip taken in California for one representative fall weekday (to capture travel related to schooling). Trip modes (e.g., walking, biking, SOV, HOV2, HOV3+, etc.) are included, as with trip purposes (e.g., work, home, shopping, school, etc.), and trip starting time as occurring in one of 5 temporal categories. Being the short-distance component of the overall CSTDM, the SDPTM only considers trips in 100 miles of length or less. For spatial resolution, California is split into 5,454 transportation analysis zones (TAZs), for which locations and sizes are based largely on the vehicle ownership, household income, and places of employment within that zone. This dataset is validated for the year 2010 and has projected values for 2050. The spatial distribution of TAZ's from the CSTDM are the same in each case and are shown below.

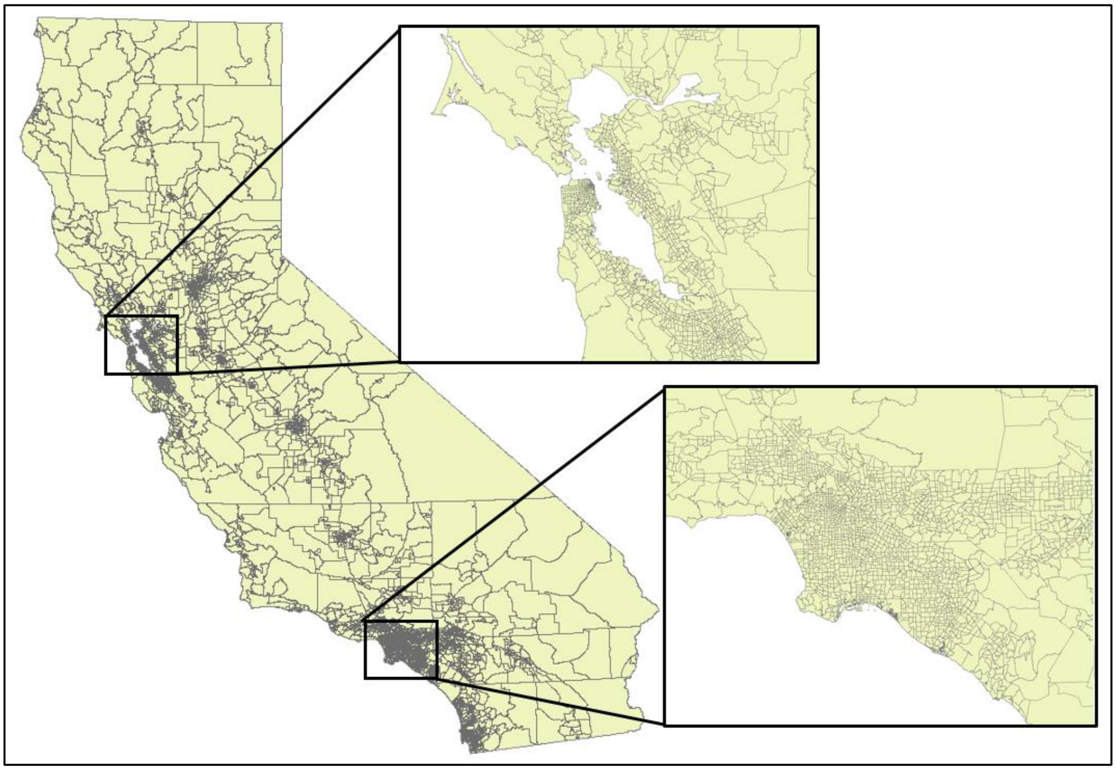


Figure 57: CSTDM Spatial TAZ Distribution

This work considers each TAZ to be a neighborhood onto itself. As mentioned, the size and location of a TAZ is largely dependent on several factors relating to housing and work. The result is that some TAZs may have many employment opportunities, but little housing or vice-versa, and therefore not fit the expectation for what a neighborhood appears to be. For example, if a TAZ is located as part of a relatively industrial area, it may seem to contradict the meaning of neighborhood. Regardless, intra-zonal trips taken by LDV in that area would still be replaced by using the Nice-SAEV program if selected.

The Nice-SAEV program is designed to replace conventionally-driven LDV trips taken for short, intra-neighborhood journeys. Therefore, the entire SDPTM is filtered such that only the trips with the same origin and destination, and the trips taken with the modes of SOV, HOV2, or HOV3+ modes are considered. Note that while the scope of the Nice-SAEV program fits appropriately in the context of this work as it provides a use-case for SAEV deployment throughout California, it begins with the goal of conventionally-driven vehicle replacement within neighborhoods. Please refer to the Future Work section, within the conclusions section, for information as to how this research effort could be expanded.

The temporal distribution of trips from the Caltrans CSTDM is such that each trip occurs in one in five increments, as detailed in the table below. These time increments represent, in order as shown: morning peak, mid-day, evening peak, late off-peak, and early off-peak.

Table 8: Temporal Distribution of Person-Trips for 350 SAEV Stations

Hour	**6am - 10am**	**10am - 3pm**	**3pm - 7pm**	**7pm - 3am**	**3am - 6am**
Person Trips	6232873	9069343	7975597	2978469	203456
Percent	23.7%	34.5%	30.4%	11.3%	0.8%

For the Nice-SAEV program, the person-trip demand for increments are assumed to be evenly distributed throughout their respective hours. The resulting person-trip demand is shown in the figure below.

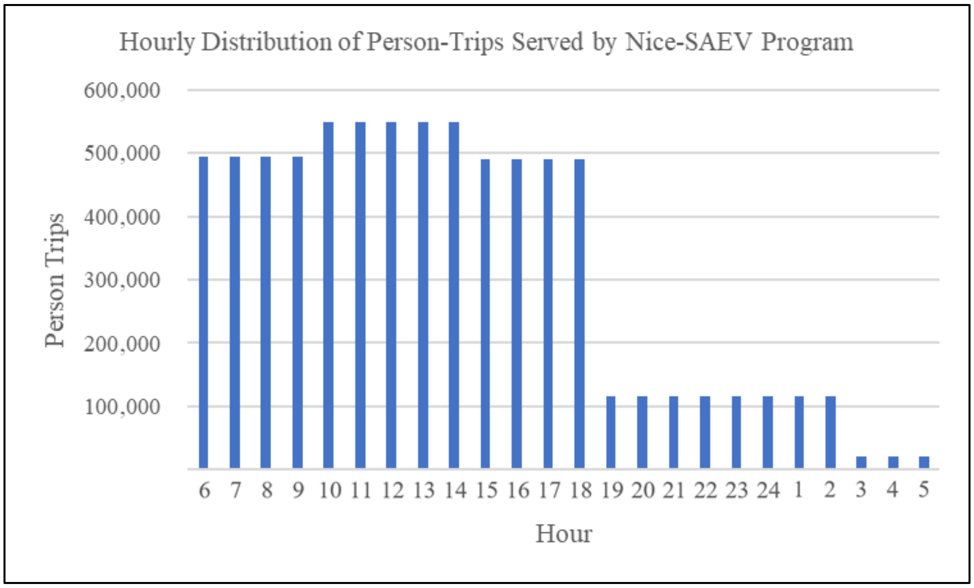


Figure 58: Hourly Distribution of Person-Trips Served by Nice-SAEV Program

Note that by evenly distributing the trips throughout the hours, there are no distinct morning and evening peaks, as seen in common temporal vehicle-trip distribution graphs, such as the image below from the 2017 National Household Travel Survey [168].

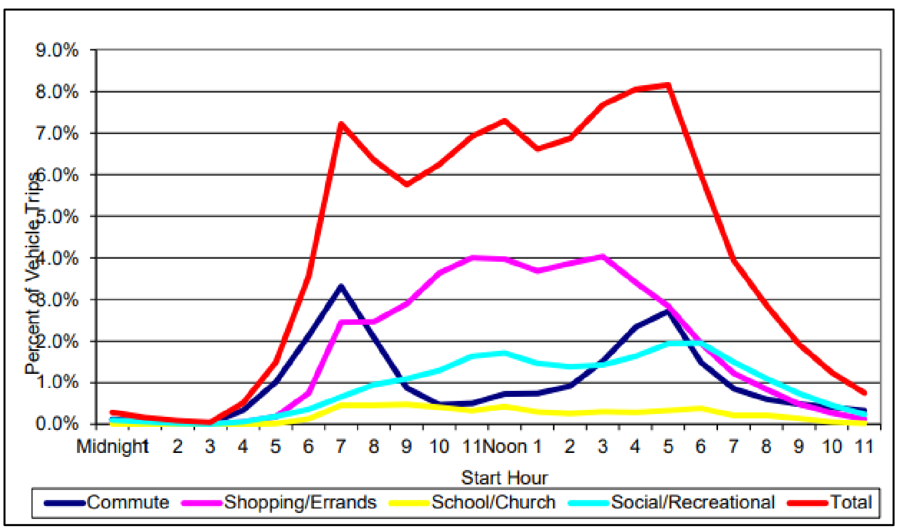


Figure 59: Temporal Vehicle Trips Distribution by Trip Purpose, 2017 NHTS

The commuting line represents mostly work-based trips for this dataset, which altogether represent approximately 31% of all trips shown. For weekend travel behavior, the 2017 estimates that just 11% of trips are work based, thus reducing these commuting peaks and evening the overall temporal graph of trips shown. The trips served by the Nice-SAEV program are calculated to be just 6.4% work based, reflecting this same behavior. To note, while this national trend was shared by the NHTS, such peak-less non-work-based (i.e., weekend) travel behavior was also observed in various California cities by Chinkin et al., using loop detector data [169].

5.2 SAEV Station Siting for California

The siting of each SAEV Station will be based on the number of trips occurring in each neighborhood (the trip-number weighted centroids of which will serve as demand points), and the proximity of each candidate site to these demand points, as described below. Therefore, the relative weight of each neighborhood is of critical importance to the siting of each SAEV Station. Note that the 2010 case is provided as a means of comparison, and that the 2050 case will ultimately be used as the basis of the energy and environmental analysis.

5.1.1.1 Spatial Intra-Neighborhood Trip Distribution for 2010

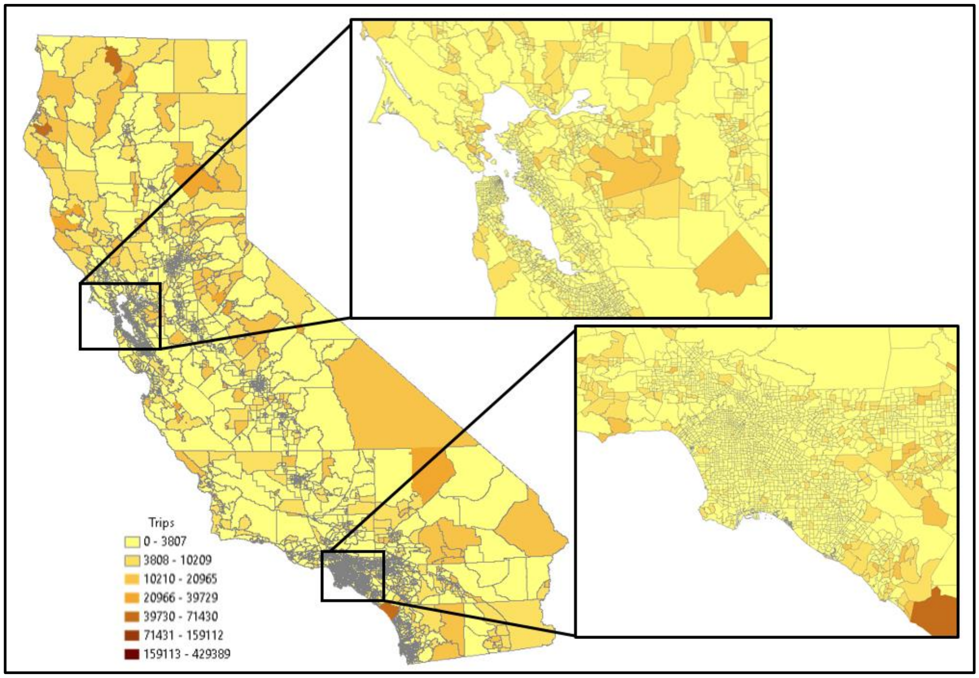


Figure 60: Spatial Intra-Neighborhood Trip Distribution for 2010

5.1.1.2 Spatial Trip Distribution for 2050

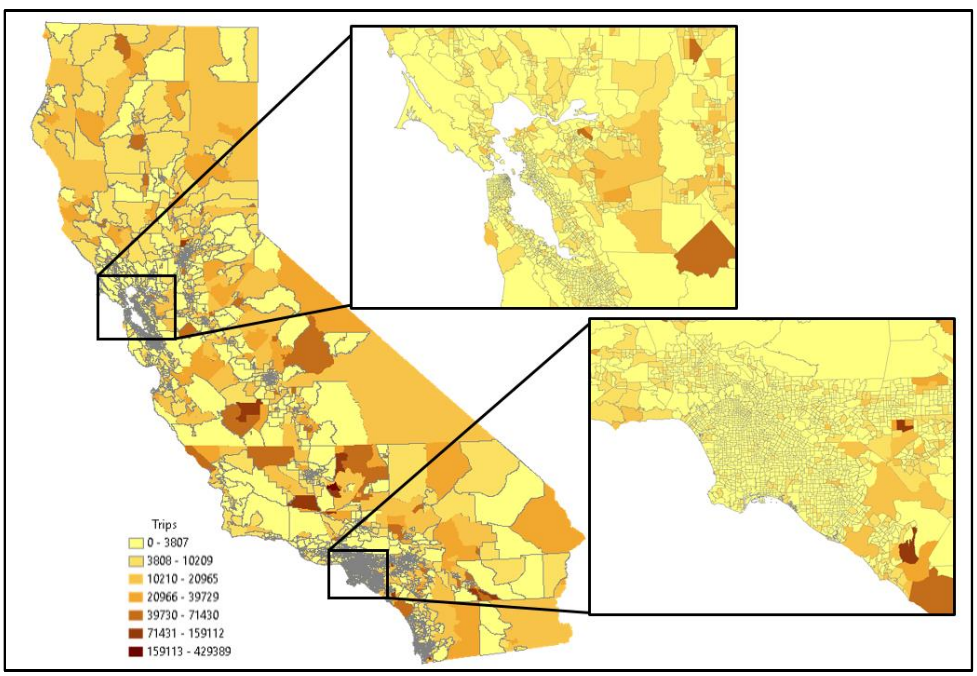


Figure 61: Spatial Intra-Neighborhood Trip Distribution for 2050

While there is a general increase in number of intra-neighborhood SOV, HOV2, and HOV3+ person-trips taken between the 2010 and 2050 datasets, there is little change in temporal trip distribution, and minimal projected change in intra-neighborhood mode choice.

The spatial distribution and measured of activity for person-trips throughout California for each neighborhood is represented as a geometrically-located centroid within each TAZ. The candidate sites are represented as points throughout California. For the 2050 case, the projected trip activity for 2050 is shown below with TAZ centroids as black diamonds, candidate sites as green dots.

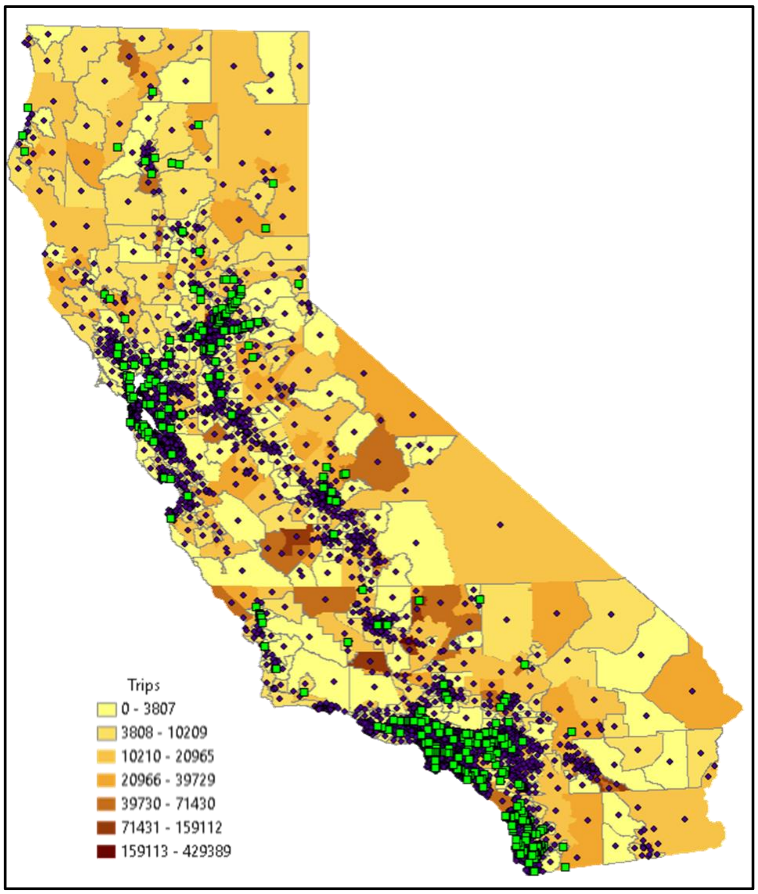


Figure 62: SAEV Station Demand Points and Candidate Sites, 2050 Scenario

5.2.1 SAEV Station Siting

In order to ensure the success of the Nice-SAEV program, the placement of SAEV stations must be prioritized to maximize the efficient allocation of SAEVs for the greatest conventional vehicle replacement. To perform this stage, the weight of total intra-neighborhood trips for SOVs and HOVs is used as the weight for a Maximize-Coverage ArcGIS Station-Allocation, subject to a 10-minute travel time impedance (such that the SAEV does not take excessively long traveling between TAZ and Station). Note that the travel time impedance assumes free-flow traffic conditions. The top 10 locations to place SAEV stations based on these criteria are illustrated in the figure below for the 2010 and 2050 cases.

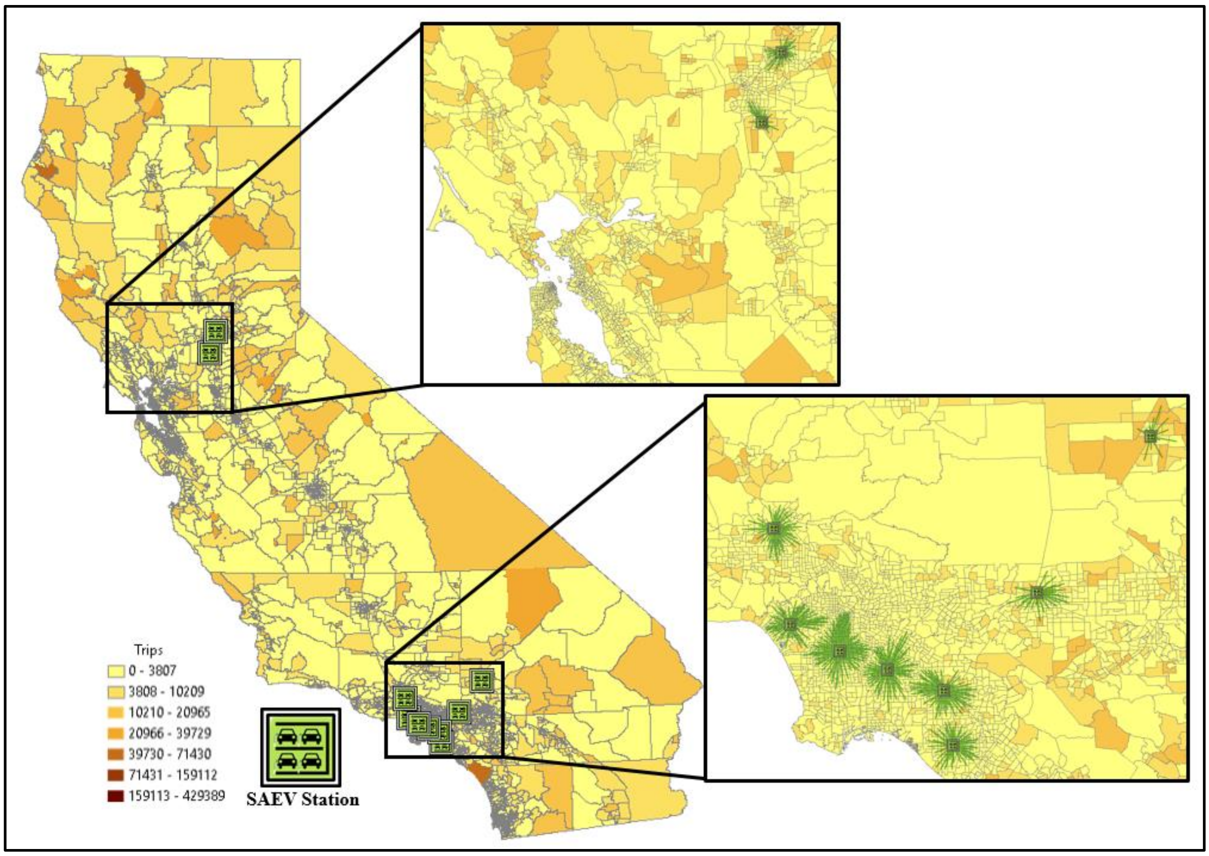


Figure 63: Siting of First 10 SAEV Stations, 2010 Scenario

Anticipating a full-rollout of Nice-SAEV program, a large-scale deployment of 350 stations throughout California would appear as below using the same siting criteria for 2010.

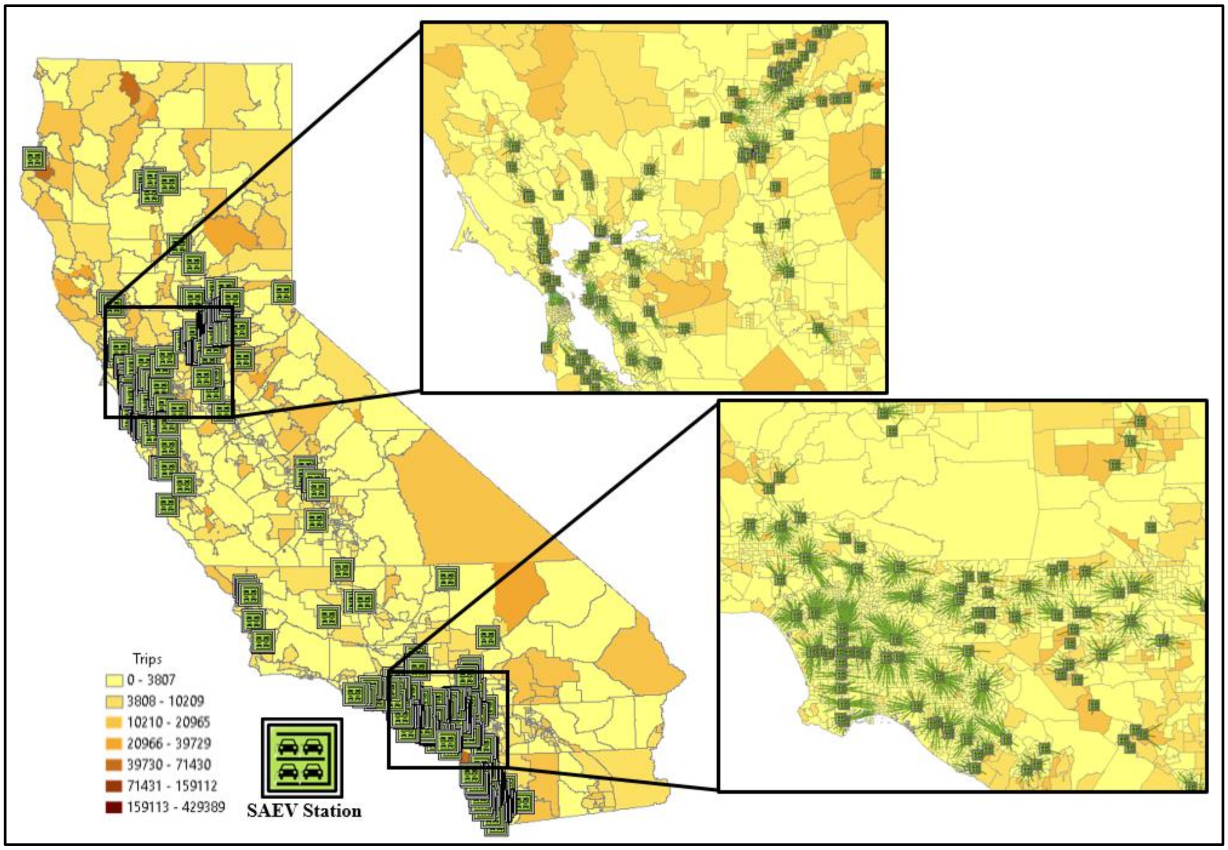


Figure 64: Siting of 350 SAEV Stations, 2010 Scenario

Siting the first ten stations for the projected 2050 trip activity would result in the following sites chosen.

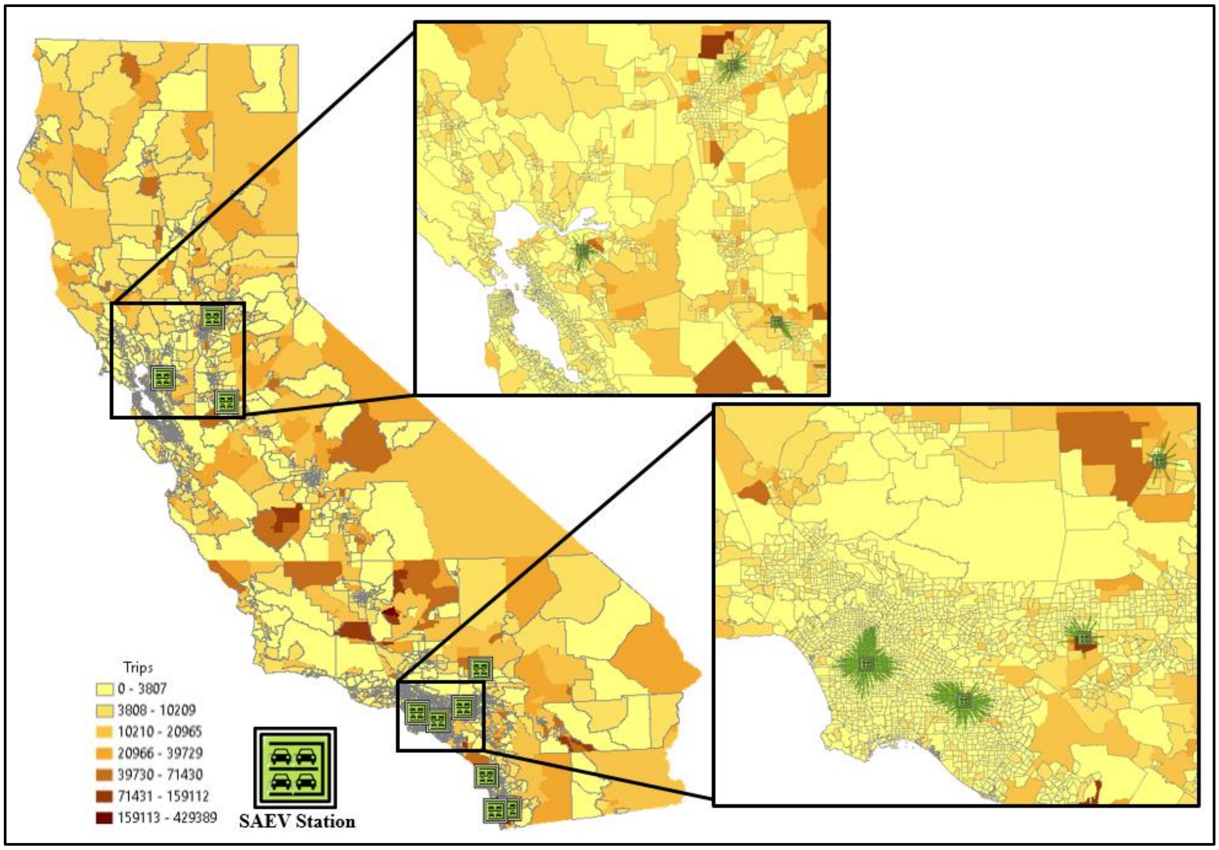


Figure 65: Siting of First 10 SAEV Stations, 2050 Scenario

As was conducted for the 2010 case, the final 2050 case for the large-scale deployment of 350 stations would result in the chosen sites as illustrated below.

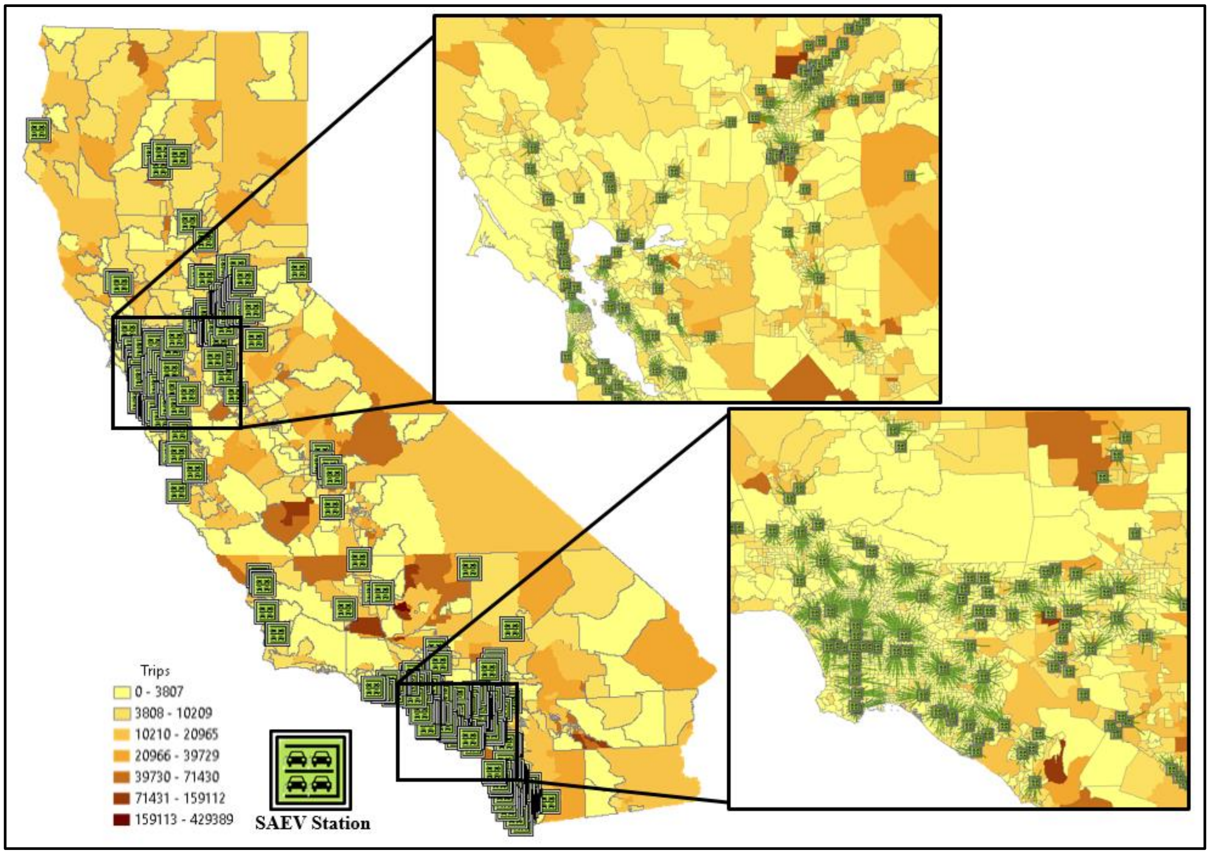


Figure 66: Siting of 350 SAEV Stations, 2050 Scenario

Note that the lines drawn between SAEV Stations and neighborhoods are simply for illustrating the allocations between Station and neighborhood. The calculations for time and distance constraints in ArcGIS were based on a circa-2010 dataset of California streets, which can be seen at the underlying grey lines below. This dataset includes accurate speed limits on residential roads and highways, which allows for the measurement of station-to-neighborhood distances, and corresponding travel times. Also note that, as indicated below, these allocation lines indicate that stations are chosen to serve TAZs which are often on a central location and near a relatively high-speed roadway. A closer view of stations sited in Southern California in the 2050-350 station scenario is shown below.

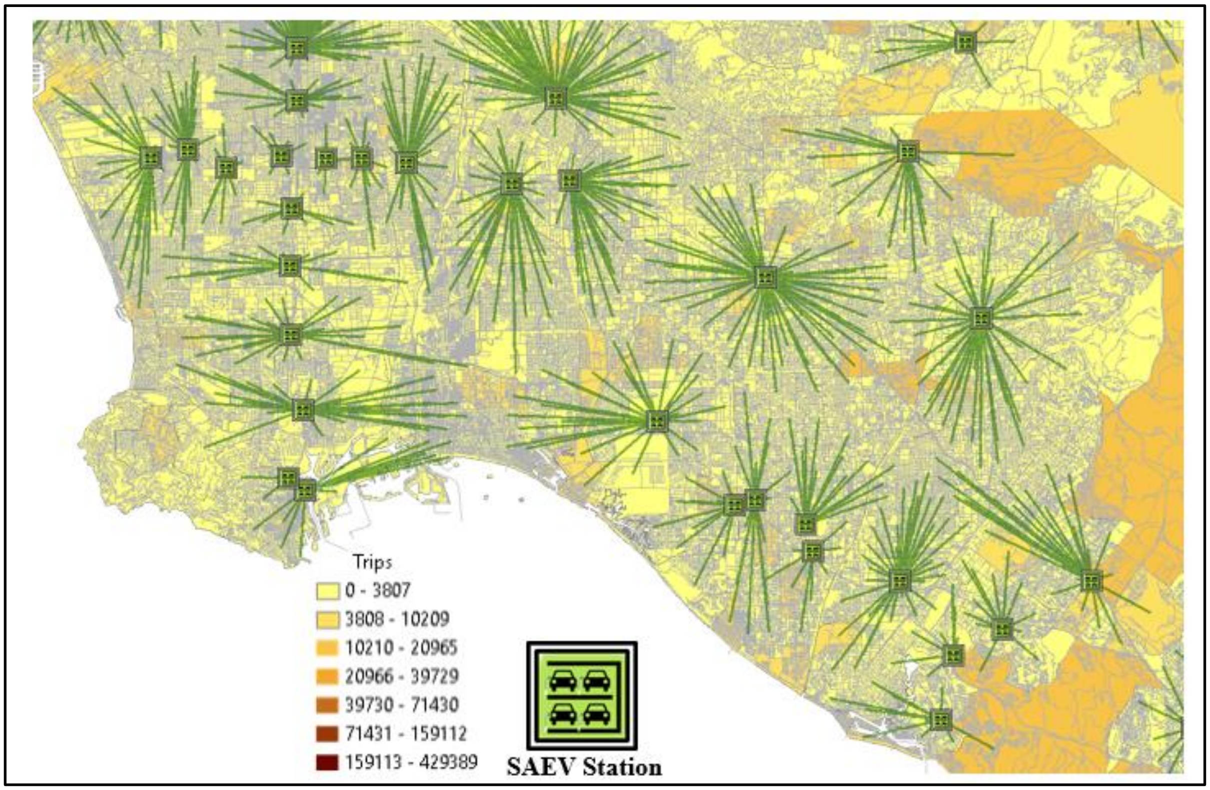


Figure 67: Close-up of SAEV Station Siting for 350 Station Scenario

5.3 SAEV Fleet Sizing: Nice-SAEV Operational Properties and Deployment Examples

With SAEV Stations sited, SAEV fleets can be designed and implemented in the Nice-SAEV program. As mentioned in the previous section, the 2050 scenario will form the basis for energy and environmental calculations, and as a result, only the 2050 case will be used to analyze the Nice-SAEV fleets. Furthermore, to allow for the measurement of the greatest energy and environmental impacts, the maximum 350-station scenario will be the specific 2050 scenario considered.

For the 2050-350 station scenario, there were 3,287 of the total 5,454 neighborhoods selected to correspond to the 350 stations. A total of 3,765,391 conventionally-driven vehicle miles traveled are displaced by adopting the Nice-SAEV program for this scenario, accounting for approximately 14% of the intra-neighborhood VMT for SOV, HOV2, and HOV3+ mode choices. Note, that the siting of SAEV-Stations for this analysis favors relatively small neighborhoods, and neighborhoods that are already in proximity to current Park-and-Ride facilities. This means that relatively large neighborhoods with correspondingly large VMT within are not considered by the Nice-SAEV scenario as outlined. For example, the average intra-neighborhood trip distance across all 5,454 neighborhoods is 0.84 miles, with a median intra-neighborhood trip distance of 0.37 miles. For the 3,287 neighborhoods served by the Nice-SAEV program, the average intra-neighborhood trip distance is less than half at 0.40 miles, yet with a slightly less median intra-neighborhood trip distance of 0.33 miles. Therefore, while the overall percent SAEV-served VMT appears small, the relatively large rural neighborhoods disproportionately account for the majority of intra-neighborhood VMT. This is an important consideration, as these rural neighborhoods would be less likely to benefit from the sharing of vehicles anyway, as the reduced spatial trip-density for the service area would reduce the likelihood for trip sharing. Meaning, that the Nice-SAEV stations as sited would serve a more significant portion of the realistically attainable VMT than would be evident just looking at the 14% figure.

For a closer look at how the SAEV Stations operate, refer to the close-up image of an example station below.

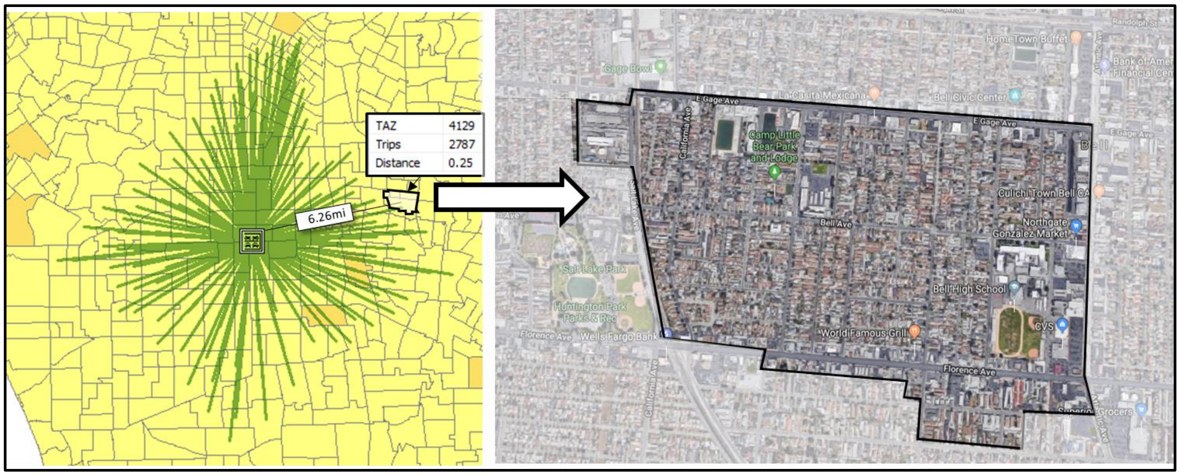


Figure 68: Example SAEV Station with Emphasized Neighborhood, TAZ, Map Image Courtesy of Google, © 2019

Nearly all SAEV Stations serve multiple neighborhoods. Each neighborhood is defined to have a distance from the station (shown above as 6.26 miles, measured via shortest-path roadway), an intra-neighborhood trip distance (measured in the CSTDM as 1/3 of the square root of the neighborhood area), and the number and time of trips. For the following deployment examples, the Micro and Large-SAEV prototypes are chosen to serve as examples to demonstrate the widest properties of the designs considered: relatively high and low-efficiency, range, and ridesharing capacity.

The overall method for deploying SAEV fleets is the same for Micro and Large-SAEVs. The total number of person-trips per hour are assumed to all be served by the Nice-SAEV program, and the spatial demand for these trips is evenly distributed throughout the service area. The station-to-neighborhood distances are averaged across all participating neighborhoods, and the intra-neighborhood trip distances are averaged as well. As mentioned, intra-neighborhood distances are approximately 0.40 miles. The standard deviation for this value is 0.29 miles, yielding a coefficient of deviation (Standard Deviation / Mean) of 0.73, indicating a relatively low-varying dataset as it is a value less than one. The average distance between station and neighborhood is 3.42 miles, with a standard deviation of 1.64 miles and a corresponding low-varying coefficient of deviation of 0.48. Therefore, averaging these values to represent the larger system as a whole is a relatively reasonable exercise.

Since SAEVs are largely covering urban areas, the average speed of the vehicles is assumed to by 17 miles per hour for each total hour. This value is based on a California Air Resources Board (CARB) report on the Emissions Factor (EMFAC) Model, which assumes various speeds for certain vehicles based on occupation, and compares these values with a University of California, Riverside study into the same matter as shown below [170].

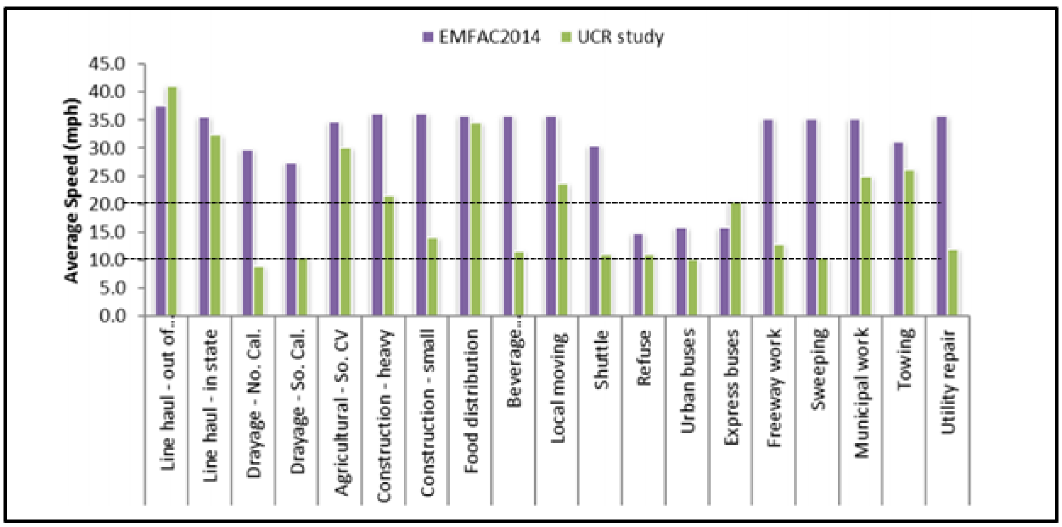


Figure 69: EMFAC2014 vs UCR Study Average Speed by Vocation-Region Group, Lines for Emphasis Added [170]

Each vehicle, as a result, will decrease in range by the same 17 miles, in each hour. However, the efficiency of the vehicle will correspond to the range the vehicle can travel before returning to the station recharging or refueling, ultimately playing a role in the later energy and environmental impact analysis.

The logic of the SAEVs deploying is such that the SAEVs are dispatched to serve the hourly person-trip demand, which is assumed to be evenly-distributed throughout the hour. An initial “group” of SAEVs from the overall fleet will be dispatched to meet the first person-trips of the day at 6:00 AM. When demand grows towards the middle of the day, or when the initial group of SAEVs are low on range and need to get replaced, additional SAEV groups will be deployed to serve the person-trip demand. If the total SAEV fleet deployed in neighborhoods is in excess of the number required to serve demand, the SAEVs with the lowest range will return to the station immediately, as to begin charging or fueling once again and to prevent needlessly crowding the participating neighborhoods. These operational characteristics serve as a consistent framework for which to base the following Nice-SAEV deployment scenarios.

5.3.1 Micro SAEV Fleet Deployment

The following diagram illustrates the deployment Micro-SAEVs for use in the Nice-SAEV program, for the projected 2050 person-trips and using 350 stations.

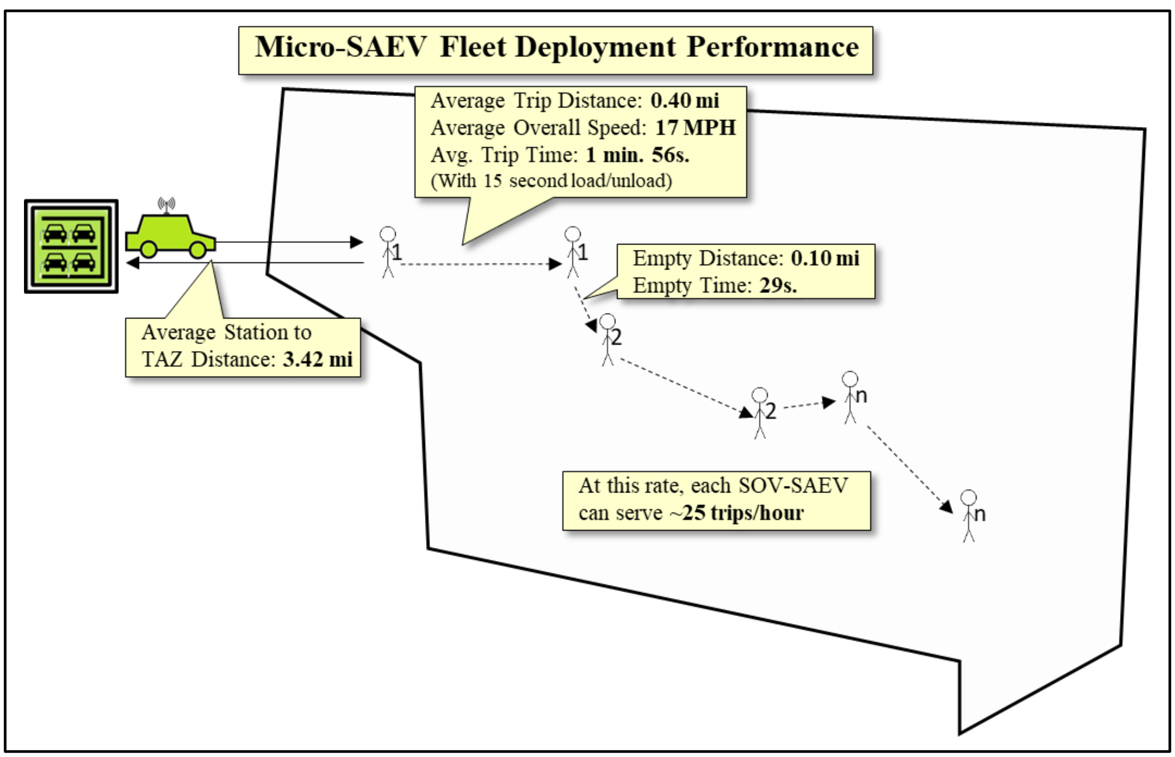


Figure 70: Micro-SAEV Fleet Deployment Performance Illustration

For the case of the BEV Micro-SAEV, there is no capacity for ridesharing. Studies have estimated the additional VMT associated with looking for a new passenger from a former passenger to be between 5-10% under optimal conditions in moderately-sized city environments [72], [171]. Presently, the empty VMT for TNC drivers between passengers has been averaged at 39% across five cities, with Los Angeles drivers adding an average of 35.8% VMT in search of new passengers (i.e., deadheading) [172]. A later study by Henao et al. affirmed these results with their own study using TNC and passenger survey data, concluding that VMT would increase by at least 40.8% [173]. All these studies were performed on city-scale and assumed similar network performance (e.g., reasonable taxi-like wait times of approximately 5 minutes, similar speed limits, etc.). Conservatively, this work will estimate the additional VMT associated with searching for a new passenger at 25%. Note that this factor just accounts for the additional VMT for vehicles in search of a new passenger within the TAZ. The final VMT number will also depend on the number of SAEVs performing Station-to-TAZ trips.

5.3.1.1 BEV Micro-SAEV Fleet Deployment, Level 2 Charging Protocol

Fleets of BEV Micro-SAEVs are now able to be allocated to each hour of person-trip demand. The following figure shows the hourly trip demand, the number of BEV-SAEVs required to perform those trips, and when the vehicles would need to charge based on a Level 2 / 10kW immediate charging protocol. Note that the number of BEV-SAEVs is one-twenty-fifth of the total trips to be served in the hour. This the direct result of the assumed average speed, loading times, and extra VMT as illustrated just previously.

Hour	% of demand	Trips in Hour	# 1S BEV-SAEVs	Group 1	Range	Group 2	Range	Group 3	Range	Group 4	Range
6	5.89%	616346	24739	24739	140						
7	5.89%	616346	24739	24739	123						
8	5.89%	616346	24739	24739	106						
9	5.89%	616346	24739	24739	89						
10	6.86%	717467	28798	24739	72	4059	140				
11	6.86%	717467	28798	24739	55	4059	123				
12	6.86%	717467	28798	24739	38	4059	106				
13	6.86%	717467	28798	24739	21	4059	89				
14	6.86%	717467	28798	24739	4	4059	72				
15	7.54%	788677	31656			4059	55	27597	140		
16	7.54%	788677	31656			4059	38	27597	123		
17	7.54%	788677	31656			4059	21	27597	106		
18	7.54%	788677	31656			4059	4	27597	89		
19	1.41%	147265	5911					5911	72		
20	1.41%	147265	5911					5911	55		
21	1.41%	147265	5911					5911	38		
22	1.41%	147265	5911					5911	21		
23	1.41%	147265	5911					5911	4		
24	1.41%	147265	5911							5911	140
1	1.41%	147265	5911							5911	123
2	1.41%	147265	5911							5911	106
3	0.26%	26825	1077							1077	89
4	0.26%	26825	1077							1077	72
5	0.26%	26825	1077							1077	55

Figure 71: BEV Micro-SAEV Fleet Distribution, Level 2 Charging

For each group of SAEVs returning, there is a corresponding period when the SAEVs are set to charge, as these scenarios apply immediate charging strategies. The charging periods appear shaded, with the final fraction of charge left partially shaded. Note that the SAEVs returning with some energy still unused take less time to charge back to full battery capacity. The useful capacity for the Micro-SAEVs (i.e., the capacity minus a small buffer to prevent battery degradation, a rather common practice as of this writing), is 23.04 kWh. The total number of BEV Micro-SAEVs with a Level 2-Charging protocol required to support the network in this configuration is 56,395, or approximately 161 vehicles per SAEV Station. Current Park-and-Ride facilities range in capacity from under 10 spaces, to over 1,000, with an average capacity about 103. Therefore, this hypothetical scenario is rather reasonable. Relative to the other Nice-SAEV scenarios considered, this scenario requires the most vehicles as it operates with zero ridesharing, offers the vehicles with lowest range, and offers the slowest recovery of fleet vehicles to become reused as the vehicles charge with the slowest charging rate.

Next is the charging behavior and corresponding electricity demand profile. This hourly demand in electricity is what the California energy grid would see should the Nice-SAEV program deploy these vehicles. When charging at 10 kW, a 23.04 kWh Battery will be fully charged in about 2.3 hours, not accounting for potential inefficiency or lost time plugging and unplugging the vehicle. The Level 2 Charging profile associated with this fleet of SAEVs is shown below. Note that G1, G2, etc., refers to each Group of vehicles which altogether represent the fleet. Each group is separately deployed from the station to meet upcoming trip demand.

Hour	G1 Charging	G2 Charging	G3 Charging	G4 Charging	Vehicle-Hours (L2)	% Demand
6	0	0	0	1077	1077	1.18%
7	0	0	0	1077	473	0.52%
8	0	0	0	0	0	0.00%
9	0	0	0	0	0	0.00%
10	0	0	0	0	0	0.00%
11	0	0	0	0	0	0.00%
12	0	0	0	0	0	0.00%
13	0	0	0	0	0	0.00%
14	0	0	0	0	0	0.00%
15	24739	0	0	0	24739	27.14%
16	24739	0	0	0	24739	27.14%
17	24739	0	0	0	7328	8.04%
18	0	0	0	0	0	0.00%
19	0	4059	21686	0	12615	13.84%
20	0	4059	0	0	4059	4.45%
21	0	4059	0	0	1202	1.32%
22	0	0	0	0	0	0.00%
23	0	0	0	0	0	0.00%
24	0	0	5911	0	5911	6.48%
1	0	0	5911	0	5911	6.48%
2	0	0	5911	0	1751	1.92%
3	0	0	0	4834	1347	1.48%
4	0	0	0	0	0	0.00%
5	0	0	0	0	0	0.00%

Figure 72: BEV Micro-SAEV Grid Demand Profile, Level 2 Charging

The term "Vehicle-Hours" refers to the number of vehicles charging in the SAEV Station at that hour, multiplied by the battery capacity left to charge of the total vehicles in the station at that given time. In other words, the 1077 vehicles charging at 6 A.M. from Group 4 all require their hour of charge, and there are 1077 vehicle-hours as a result. However, for the next hour, the SAEVs are nearly full and have just a fraction of the hourly charge time remaining, approximately 44% of the hour. As a result, the electricity the grid needs to provide those vehicles in that hour is equivalent to 44% of the 1077 vehicle fleet, or 473 vehicle-hours' worth of energy.

As illustrated, not all vehicles would require chargers at the same time. The number of chargers required to support these vehicles is the maximum charging in the preceding figure, 24,739. This averages to approximately 71 chargers per station. Assuming the average station consists of about 103 spaces, the chargers for these BEV Micro-SAEVs could theoretically be placed in the Park-and-Ride lots themselves, while any excess vehicles could potentially be parked in open lots nearer to their respective neighborhoods.

5.3.1.2 BEV Micro-SAEV Fleet Deployment, Level 3 Charging Protocol

The next proposed fleet deployment for the Nice-SAEV program uses the same BEV Micro-SAEVs, but with a Level 3, 50 kW immediate charging protocol. Please refer to the figure below for an illustration of the groups of vehicles required and associated charging behavior.

Hour	% of demand	Trips in Hour	# 1S BEV-SAEVs	Group 1	Range	Group 2	Range	Group 3	Range	Group 4	Range
6	5.89%	616346	24739	24739	140						
7	5.89%	616346	24739	24739	123						
8	5.89%	616346	24739	24739	106						
9	5.89%	616346	24739	24739	89						
10	6.86%	717467	28798	24739	72	4059	140				
11	6.86%	717467	28798	24739	55	4059	123				
12	6.86%	717467	28798	24739	38	4059	106				
13	6.86%	717467	28798	24739	21	4059	89				
14	6.86%	717467	28798	24739	4	4059	72				
15	7.54%	788677	31656			4059	55	27597	140		
16	7.54%	788677	31656			4059	38	27597	123		
17	7.54%	788677	31656			4059	21	27597	106		
18	7.54%	788677	31656			4059	4	27597	89		
19	1.41%	147265	5911					5911	72		
20	1.41%	147265	5911					5911	55		
21	1.41%	147265	5911					5911	38		
22	1.41%	147265	5911					5911	21		
23	1.41%	147265	5911					5911	4		
24	1.41%	147265	5911							5911	140
1	1.41%	147265	5911							5911	123
2	1.41%	147265	5911							5911	106
3	0.26%	26825	1077							1077	89
4	0.26%	26825	1077							1077	72
5	0.26%	26825	1077							1077	55

Figure 73: BEV Micro-SAEV Fleet Distribution, Level 3 Charging

Note that the same number of vehicles is required in this Level 3 charging scenario as with the Level 2 scenario, due to a peak in trip demand in the middle of the day that corresponds with the return of the first group of vehicles. The faster charging time of approximately 30 minutes may have been able to prevent the additional 27,597 SAEVs to meet demand had there been a bit more overlap from longer range, or lessened demand. The number of total SAEVs required for this scenario is therefore 56,395. This result underscores the importance of exploring fleet management options in future efforts, as detailed more in the Future Work section of the Conclusions. The corresponding charging profile for this Level 3 BEV Micro-SAEV is shown below.

Hour	G1 Charging	G2 Charging	G3 Charging	G4 Charging	Vehicle-Hours (L3)	% Demand
6	0	0	0	1077	311	1.52%
7	0	0	0	0	0	0.00%
8	0	0	0	0	0	0.00%
9	0	0	0	0	0	0.00%
10	0	0	0	0	0	0.00%
11	0	0	0	0	0	0.00%
12	0	0	0	0	0	0.00%
13	0	0	0	0	0	0.00%
14	0	0	0	0	0	0.00%
15	24739	0	0	0	11107	54.29%
16	0	0	0	0	0	0.00%
17	0	0	0	0	0	0.00%
18	0	0	0	0	0	0.00%
19	0	4059	21686	0	5765	28.18%
20	0	0	0	0	0	0.00%
21	0	0	0	0	0	0.00%
22	0	0	0	0	0	0.00%
23	0	0	0	0	0	0.00%
24	0	0	5911	0	2654	12.97%
1	0	0	0	0	0	0.00%
2	0	0	0	0	0	0.00%
3	0	0	0	4834	621	3.03%
4	0	0	0	0	0	0.00%
5	0	0	0	0	0	0.00%

Figure 74: BEV Micro-SAEV Grid Demand Profile, Level 3 Charging

While the number of vehicles is the same, the number of chargers required is less, due to the charging time being less than one hour. While 24,739 vehicles require a charge at 3:00 P.M., the charging time is less than 30 minutes for each vehicle. As such, assuming a minimal time for vehicles to navigate to and from chargers, there would be approximately 50 chargers required per station assuming the same immediate charging protocol. Please note that there are further potential research avenues to explore in this context as mentioned in the Future Work section. Note as well that the values in the vehicle-hours column are significantly less than the Level 2 scenario. This does not mean that less energy going into the vehicles, but rather that the rate of energy entering the vehicles is much greater. Again, where the Level 2 scenario would take 2.3 hours to fully charge a depleted vehicle, this Level 3 protocol would take just under 30 minutes.

5.3.1.3. FCEV Micro-SAEV Fleet Behavior and Fueling Demand Profile

Next, FCEV-powered Micro-SAEVs are evaluated for fleet behavior and fueling. Note the longer range, and corresponding impact on duration of service below.

Hour	% of demand	Trips in Hour	# 1S FCEV-SAEVs	Group 1	Range	Group 2	Range	Group 3	Range	Group 4	Range	Group 5	Range
6	5.89%	616346	24739	24739	235								
7	5.89%	616346	24739	24739	218								
8	5.89%	616346	24739	24739	201								
9	5.89%	616346	24739	24739	184								
10	6.86%	717467	28798	24739	167	4059	235						
11	6.86%	717467	28798	24739	150	4059	218						
12	6.86%	717467	28798	24739	133	4059	201						
13	6.86%	717467	28798	24739	116	4059	184						
14	6.86%	717467	28798	24739	99	4059	167						
15	7.54%	788677	31656	24739	82	4059	150	2858					
16	7.54%	788677	31656	24739	65	4059	133	2858					
17	7.54%	788677	31656	24739	48	4059	116	2858					
18	7.54%	788677	31656	24739	31	4059	99	2858					
19	1.41%	147265	5911	0	14	3053	82	2858					
20	1.41%	147265	5911			3053	65	2858	235				
21	1.41%	147265	5911			3053	48	2858	218				
22	1.41%	147265	5911			3053	31	2858	201				
23	1.41%	147265	5911			3053	14	2858	184				
24	1.41%	147265	5911					2858	167	3053	235		
1	1.41%	147265	5911					2468	150	3053	218	390	235
2	1.41%	147265	5911					2468	133	3053	201	390	218
3	0.26%	26825	1077					0	116	687	184	390	201
4	0.26%	26825	1077					0	99	687	167	390	184
5	0.26%	26825	1077					0	82	687	150	390	167

Figure 75: FCEV Micro-SAEV Fleet Distribution

The enhanced range of the FCEV Micro-SAEVs is an important characteristic for serving the trip demand throughout the day. Relative to the BEV Micro-SAEVs, the FCEV powertrain can sustain service through the peak in demand, thus avoiding the necessity of a large group of SAEVs deploying in the mid-day peak. The resulting number of vehicles required to support the Nice-SAEV program with these prototype FCEVs is 31,656, a significant reduction from the BEV cases presented. This is largely a factor of the longer range to serve the demand given, but could, in another circumstance, be also due to the fast refueling. For example, if the range of the FCEV was to be 146.6 miles, as the BEV Micro-SAEVs, the fast-refueling time may have helped get SAEVs back on the road faster than even the approximately 30-minute delay of the Level 3, 50 kW BEV SAEVs.

For refueling behavior, note that the temporal distribution of fueling does not necessarily have to be coupled to the surrounding energy infrastructure. In other words, the hydrogen necessary to support this SAEV fleet can be generated when most economically beneficial and stored for final use. Please refer to the temporal fueling distribution below.

Hour	G1 Fueling	G2 Fueling	G3 Fueling	G4 Fueling	G5 Fueling	Vehicle-Hours (FC)	% Demand
6	0	0	0	687	390	25	1.42%
7	0	0	0	0		0	0.00%
8	0	0	0	0		0	0.00%
9	0	0	0	0		0	0.00%
10	0	0	0	0		0	0.00%
11	0	0	0	0		0	0.00%
12	0	0	0	0		0	0.00%
13	0	0	0	0		0	0.00%
14	0	0	0	0		0	0.00%
15	0	0	0	0		0	0.00%
16	0	0	0	0		0	0.00%
17	0	0	0	0		0	0.00%
18	0	0	0	0		0	0.00%
19	24739	1006	0	0		1480	82.29%
20	0	0	0	0		0	0.00%
21	0	0	0	0		0	0.00%
22	0	0	0	0		0	0.00%
23	0	0	0	0		0	0.00%
24	0	3053	0	0		192	10.68%
1	0	0	0	0		0	0.00%
2	0	0	0	0		0	0.00%
3	0	0	2468	2366		101	5.61%
4	0	0	0	0		0	0.00%
5	0	0	0	0		0	0.00%

Figure 76: FCEV Micro-SAEV Fuel Demand Profile

Note that the number of vehicle-hours calculated here assumes that it takes 4 minutes to refuel this vehicle. Being that it has a 2.5 kg hydrogen tank, this is currently a relatively conservative estimate, factoring in potential repositioning time for various vehicles. Accordingly, because numerous vehicles can refuel in one hour, there is a decrease in the minimum number of refueling spaces required. For this scenario, approximately 1716 hydrogen refueling spaces are required overall, and about 5 refueling positions required per station.

5.3.2 Large SAEV Fleet Deployment

As mentioned in Section 2.2.3 Shared Mobility Overview, researchers have found ridesharing to be a critical aspect to the sustainability of the overall autonomous vehicle-enhanced transportation network, mostly as a means of reducing VMT. Micro-SAEVs do not have the ability to offer ridesharing and must therefore increase VMT as the result of not being able to provide overlapping trips to passengers (i.e., Micro-SAEVs must serve person-trips sequentially, and travel some distance empty to reach another passenger). Large-SAEVs can convey more than one occupant and can therefore allow for passengers to participate in ridesharing (i.e., allowing multiple to ride in a single vehicle at once). Such a system could also assign vehicles to pick up additional passengers mid-trip, thus becoming a system commonly referred to as a Dynamic Ride Sharing (DRS) service [174]. The VMT impacts of such a service has been found to have an increase or decrease on VMT, though generally a decrease on VMT for studies which do not consider induced demand (i.e., the increased demand for trips coming from people who would otherwise not have been traveling) [175]. The Nice-SAEV program is one such program that does not consider induced demand, as the hypothetical scenario encompasses just the replacement of anticipated conventionally-driven vehicles from the mentioned trip purposes, and many examples of similar studies measuring VMT impacts of DRS systems replacing present travel behavior exist. For example, on the extreme end of possibility, a study of Manhattan in New York City was studied by Santi et al., who measured a maximum reduction of VMT by 40% compared to current taxi VMT with SAVs with at least a capacity of 3 [176]. A relatively large, but less trip-dense study by researchers from the International Transport Forum measured the impact of a mixed fleet of 6-passenger SAVs, with 8 and 16-passenger SAV-busses for the city of Lisbon, Portugal [177]. This SAV fleet, when displacing the entire fleet of conventionally driven vehicles (i.e., all motorized trips) for Lisbon, resulted in an overall reduction in VMT by 37%. For a scenario of just using 6-passenger SAVs, VMT decreased by 25%. A study by Amey measured the potential for commuters to MIT to participate in ridesharing, and if choosing to rideshare, what the VMT impacts would be if met using an allocation algorithm similar to a DRS fleet. They found that if the about 50-77% of eligible commuters choose to rideshare by picking up another passenger (i.e., for a total of 2 people in the vehicle), the VMT would decrease by approximately 9-27% [178]. A study from UC Davis researchers investigated research into the effect of VMT fees on induced demand using the San Francisco Chained Activity Modeling Process (SF-CHAMP), finding that for a base-case without induced demand, DRS can reduce VMT by up to 23.1% [175], [179]. In a comparison between shared and non-shared taxis for replacing home-based work trips, Burghout et al. measured the impact of autonomous taxi fleet performance (increased passenger wait time, and increased time on road) on network VMT, without pre-defining passenger capacities for the fleet of vehicles [180]. For a non-shared AV-replacement system, VMT increased by 24%. When using SAVs, VMT decreased by 11-24% for passenger wait-times of 10 minutes and 15 minutes, and maximum trip times increased by 30% and 50%, respectively. An additional study into the potential decrease of VMT as the result of a city-to-region-wide DRS system was performed by Heilig et al., who studied various transportation network impacts (e.g., VMT and total SAV Fleet size) for a region surrounding and including Stuttgart, Germany [181]. Using a scenario where 4-seat SAVs at near full-capacity replace all vehicle demand, they found that a maximum of 24% of VMT could be reduced compared to the base case of present-day VMT. Note, however, that this study allowed for transportation mode shifts (e.g., some SOV commuters switched to biking for shorter trips, etc.), and as a result, the percent of trips spent as either the driver or passenger of a vehicle decreased from approximately 57% to 39%. This is a departure from the assumption of the Nice-SAEV program, which does not change modal choices. Thus, relative to the Large-SAEV scenario, this study yields a relatively aggressive estimate of VMT reductions.

The degree to which rides can be shared (i.e., the average occupancy at any given time) depends on the passengers available to share that ride at that specific time. For example, researchers with the International Transport Forum published a study measuring the overall average occupancy of a fleet of generic HOV-SAVs, finding an increased average occupancy throughout a day with distinct peaks and lulls in ridesharing demand. The researchers also found a relatively even average vehicle occupancy when compared to the standard morning and evening peaks in demand [182]. The hourly person-trip demand for this study uses intra-TAZ travel patterns, which are approximately 93% non-work based. The resulting hourly person-trip demand is a relatively smooth when compared to standard work-based trips, which have distinct morning and evening peaks. Therefore, assuming an average vehicle capacity throughout the day for Large-SAEVs approximates such anticipated SAV-fleet behavior even more closely. Winter et al. performed a study for the Dutch city of Arnhem, in which 2, 4, 8, 10, 20, and 40-passenger SAVs were evaluated for relative passenger wait-times required, fleet size, and overall system cost [183]. For fleets of 10-passenger vehicles comparable performance characteristics of studies, the average vehicle occupancy was measured to be approximately 5 passengers throughout the day. Additional researchers have affirmed these findings, as evidenced by the aforementioned study for Lisbon, Portugal, where researchers found an average occupancy of their 8-seat SAV-bus to be 4.2 passengers [177].

The Large-SAEV scenario assumes similar performance to these studies, where an average occupancy of the 8-seat SAEVs is 4-passengers throughout the day. While the VMT increases of the Micro-SEAV scenario were based on the non-DRS (i.e., private) SAEVs, the ability for DRS means that the Large-SAEVs will be likely to reduce VMT, under the assumption that the Nice-SAEV program stays open to just the individuals who would otherwise drive or ride in vehicles. VMT reductions typical of such networks in urban settings, varying in terms of vehicle occupancy, fleet sizes, and trip density span 9-40%. The Large-SAEV scenario of the Nice-SAEV program therefore conservatively estimates an intra-zonal VMT reduction of 15%. This assumption on the lower-end of anticipated VMT reductions is in part made due to the relative average trip density of the present study and pervious works. In terms of person-trips taken per square mile within each TAZ, is measured to be 1310 person-trips/sq. mile per day for SAEVs performing trips in the Nice-SAEV program. On the extreme end of trip density, the Manhattan study by Santi et al. was performed on a network with approximately 15 times the trip density, with many trips being able to overlap one another, and thus corresponding to a 40% VMT reduction. Such VMT reduction is too great to assume reasonable for the Nice-SAEV program and a more conservative figure, more in line with the studies garnering more modest VMT reductions, is used. This Large-SAEV network performance is illustrated below.

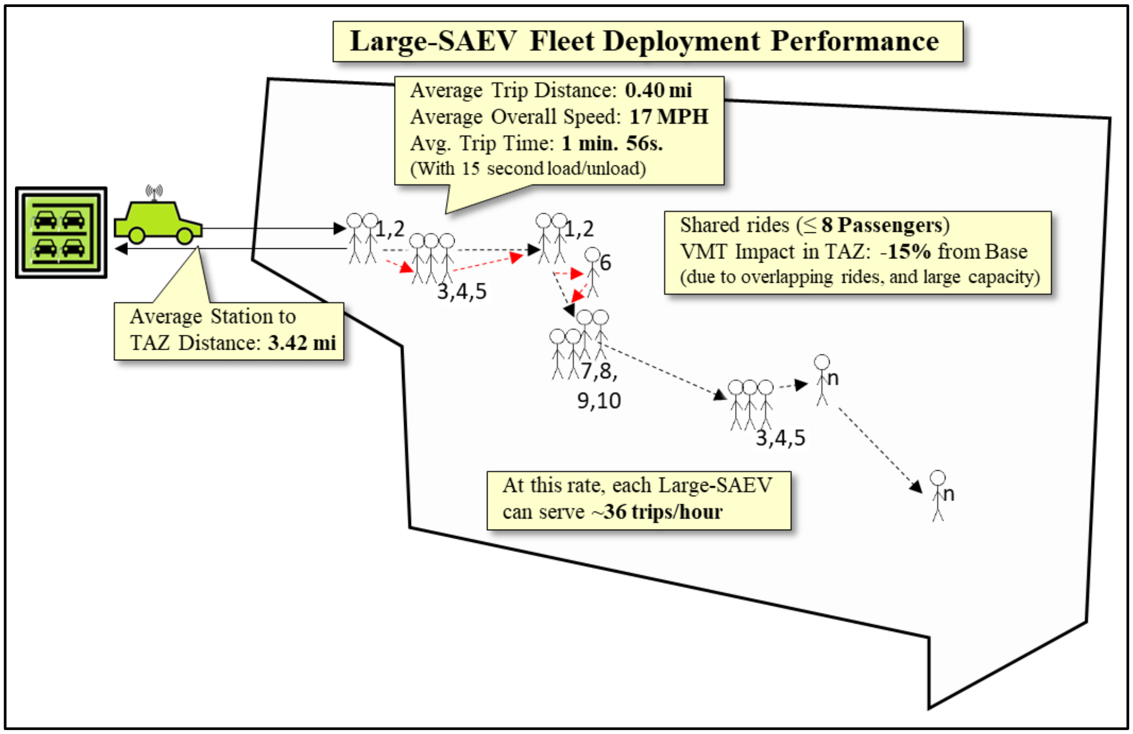


Figure 77: Large-SAEV Fleet Deployment Performance Illustration

Where the Micro-SAEVs represent the least ridesharing ability and lowest range, the ridesharing ability and high range of the Large-SAEVs immediately appear as valuable when reviewing the fleet deployment information provided below.

Hour	% of demand	Trips in Hour	# 8S BEV-SAEVs	Group 1	Range	Group 2	Range	Group 3	Range
6	5.89%	616346	16823	16823	293				
7	5.89%	616346	16823	16823	276				
8	5.89%	616346	16823	16823	259				
9	5.89%	616346	16823	16823	242				
10	6.86%	717467	19583	16823	225	2760	293		
11	6.86%	717467	19583	16823	208	2760	276		
12	6.86%	717467	19583	16823	191	2760	259		
13	6.86%	717467	19583	16823	174	2760	242		
14	6.86%	717467	19583	16823	157	2760	225		
15	7.54%	788677	21526	16823	140	2760	208	1944	293
16	7.54%	788677	21526	16823	123	2760	191	1944	276
17	7.54%	788677	21526	16823	106	2760	174	1944	259
18	7.54%	788677	21526	16823	89	2760	157	1944	242
19	1.41%	147265	4019			2075	140	1944	225
20	1.41%	147265	4019			2075	123	1944	208
21	1.41%	147265	4019			2075	106	1944	191
22	1.41%	147265	4019			2075	89	1944	174
23	1.41%	147265	4019			2075	72	1944	157
24	1.41%	147265	4019			2075	55	1944	140
1	1.41%	147265	4019			2075	38	1944	123
2	1.41%	147265	4019			2075	21	1944	106
3	0.26%	26825	732					732	89
4	0.26%	26825	732					732	72
5	0.26%	26825	732					732	55

Figure 78: BEV Large-SAEV Fleet Distribution, Level 2 Charging

Note that the increased capacity of the battery, which has a useful capacity of 87.04 kWh, requires a relatively long charging time. While the range on these vehicles is relatively long, the charging time is significant, requiring staggered charging behavior for Group 3 as some return to the station sooner than others. Due to the large range and ridesharing ability of these vehicles, just 21,527 are required to meet the person-trip demand which averages to approximately 62 per station.

The corresponding charging behavior is shown below.

Hour	G1 Charging	G2 Charging	G3 Charging	Vehicle-Hours (L2)	% Demand
6	0	2075	1212 / 732	4019	2.78%
7	0	2075	1212 / 732	4019	2.78%
8	0	2075	1212 / 732	3556	2.46%
9	0	2075	732	2807	1.94%
10	0	2075	732	2807	1.94%
11	0	2075	732	1976	1.37%
12	0	0	0	0	0.00%
13	0	0	0	0	0.00%
14	0	0	0	0	0.00%
15	0	0	0	0	0.00%
16	0	0	0	0	0.00%
17	0	0	0	0	0.00%
18	0	0	0	0	0.00%
19	16823	685	0	17508	12.10%
20	16823	685	0	17508	12.10%
21	16823	685	0	17508	12.10%
22	16823	685	0	17508	12.10%
23	16823	685	0	16914	11.69%
24	16823	0	0	16823	11.63%
1	16823	0	0	11843	8.19%
2	0	0	0	0	0.00%
3	0	2075	1212	3287	2.27%
4	0	2075	1212	3287	2.27%
5	0	2075	1212	3287	2.27%

Figure 79: BEV Large-SAEV Grid Demand Profile, Level 2 Charging

The number of chargers required to support the BEV Large-SAEV fleet with a Level 2 charging protocol is 17,508, which equals the maximum number of vehicle-hours for this scenario. Each station on average would need 50 chargers to support this fleet. A clear and comprehensive comparison between SAEV fleet deployments is described in the final section of this chapter.

5.3.2.2. BEV Large-SAEV Fleet Behavior and Level 3 Charging Profile

The following figure illustrates the vehicle deployment of Level-3 charging BEV Large-SAEVs. As was the case with the Micro-SAEVs, the fleet deployments for this scenario yielded the same size and timing of vehicle groups as the Level 2 charging SAEVs, 21,527.

Hour	% of demand	Trips in Hour	# 8S BEV-SAEVs	Group 1	Range	Group 2	Range	Group 3	Range
6	5.89%	616346	16823	16823	293				
7	5.89%	616346	16823	16823	276				
8	5.89%	616346	16823	16823	259				
9	5.89%	616346	16823	16823	242				
10	6.86%	717467	19583	16823	225	2760	293		
11	6.86%	717467	19583	16823	208	2760	276		
12	6.86%	717467	19583	16823	191	2760	259		
13	6.86%	717467	19583	16823	174	2760	242		
14	6.86%	717467	19583	16823	157	2760	225		
15	7.54%	788677	21526	16823	140	2760	208	1944	293
16	7.54%	788677	21526	16823	123	2760	191	1944	276
17	7.54%	788677	21526	16823	106	2760	174	1944	259
18	7.54%	788677	21526	16823	89	2760	157	1944	242
19	1.41%	147265	4019			2075	140	1944	225
20	1.41%	147265	4019			2075	123	1944	208
21	1.41%	147265	4019			2075	106	1944	191
22	1.41%	147265	4019			2075	89	1944	174
23	1.41%	147265	4019			2075	72	1944	157
24	1.41%	147265	4019			2075	55	1944	140
1	1.41%	147265	4019			2075	38	1944	123
2	1.41%	147265	4019			2075	21	1944	106
3	0.26%	26825	732					732	89
4	0.26%	26825	732					732	72
5	0.26%	26825	732					732	55

Figure 80: BEV Large-SAEV Fleet Distribution, Level 3 Charging

Note that it is not necessarily always the case for the same number of SAEVs to be required despite a lower downtime. There is a general benefit for having minimal downtime (e.g., fast recharging or refueling), as a minimal downtime would maximize the opportunities for a group of SAEVs to enter back into neighborhoods and serve trips. The resulting charging behavior of this fleet deployment is seen below.

Hour	G1 Charging	G2 Charging	G3 Charging	Vehicle-Hours (L3)	% Demand
6	0	0	732	732	3.58%
7	0	0	732	542	2.65%
8	0	0	0	0	0.00%
9	0	0	0	0	0.00%
10	0	0	0	0	0.00%
11	0	0	0	0	0.00%
12	0	0	0	0	0.00%
13	0	0	0	0	0.00%
14	0	0	0	0	0.00%
15	0	0	0	0	0.00%
16	0	0	0	0	0.00%
17	0	0	0	0	0.00%
18	0	0	0	0	0.00%
19	16823	685	0	17149	83.83%
20	16823	0	0	11848	57.92%
21	0	0	0	0	0.00%
22	0	0	0	0	0.00%
23	0	0	0	0	0.00%
24	0	0	0	0	0.00%
1	0	0	0	0	0.00%
2	0	0	0	0	0.00%
3	0	2075	1212	3287	16.07%
4	0	2075	1212	2435	11.90%
5	0	2075	1212	0	0.00%

Figure 81: BEV Large-SAEV Grid Demand Profile, Level 3 Charging

Though the number of Large-SAEVs required to support the Nice-SAEV program remained the same despite increasing the charging rate, the number of chargers required decreases slightly. Assuming a minimal time to re-position SAEVs at chargers, the faster charging protocol could finish the group of 685 vehicles in less than one hour, resulting in the lower overall vehicle-hours measurement, and thus resulting in an overall number of charging spaces for Large-SAEVs to become 17,149, or approximately 49 per station.

5.3.2.3. FCEV Large-SAEV Fleet Behavior and Fueling Demand Profile

Below is the fleet-deployment for the FCEV Large-SAEV fleet. Note that the same number of vehicles is required for this scenario as was the case for both BEV scenarios at 21,527

SAEVs. This is largely due to the rather similar vehicle range, which for both vehicle types more than able to perform trips through the morning and mid-day peak of person-trips.

Hour	% of demand	Trips in Hour	# 8S FCEV-SAEVs	Group 1	Range	Group 2	Range	Group 3	Range
6	5.89%	616346	16823	16823	318				
7	5.89%	616346	16823	16823	301				
8	5.89%	616346	16823	16823	284				
9	5.89%	616346	16823	16823	267				
10	6.86%	717467	19583	16823	250	2760	318		
11	6.86%	717467	19583	16823	233	2760	301		
12	6.86%	717467	19583	16823	216	2760	284		
13	6.86%	717467	19583	16823	199	2760	267		
14	6.86%	717467	19583	16823	182	2760	250		
15	7.54%	788677	21526	16823	165	2760	233	1944	318
16	7.54%	788677	21526	16823	148	2760	216	1944	301
17	7.54%	788677	21526	16823	131	2760	199	1944	284
18	7.54%	788677	21526	16823	114	2760	182	1944	267
19	1.41%	147265	4019			2075	165	1944	250
20	1.41%	147265	4019			2075	148	1944	233
21	1.41%	147265	4019			2075	131	1944	216
22	1.41%	147265	4019			2075	114	1944	199
23	1.41%	147265	4019			2075	97	1944	182
24	1.41%	147265	4019			2075	80	1944	165
1	1.41%	147265	4019			2075	63	1944	148
2	1.41%	147265	4019			2075	46	1944	131
3	0.26%	26825	732					732	114
4	0.26%	26825	732					732	97
5	0.26%	26825	732					732	80

Figure 82: FCEV Large-SAEV Fleet Distribution

A difference to note between the BEV and FCEV fleets is the difference in range remaining for each. Specifically, the first group of FCEV Large-SAEVs returns to the SAEV station with 114 miles of range left. By comparison, 89 miles remain for the BEV-SAEV. Aside from being less dependent on frequent fueling, this enhanced range would also lead to more potential service opportunities should another construct be considered by future researchers. The following figure illustrates the fueling behavior of this fleet of FCEV Large-SAEVs.

Total SAEVs out	Out/Needed	Hour	G1 Fueling	G2 Fueling	G3 Fueling	Vehicle-Hours (FC)	% Demand
16,823	0	**6**	0	0	732	55	3.88%
16,823	0	**7**	0	0	0	0	0.00%
16,823	0	**8**	0	0	0	0	0.00%
16,823	0	**9**	0	0	0	0	0.00%
19,583	0	**10**	0	0	0	0	0.00%
19,583	0	**11**	0	0	0	0	0.00%
19,583	0	**12**	0	0	0	0	0.00%
19,583	0	**13**	0	0	0	0	0.00%
19,583	0	**14**	0	0	0	0	0.00%
21,527	0	**15**	0	0	0	0	0.00%
21,527	0	**16**	0	0	0	0	0.00%
21,527	0	**17**	0	0	0	0	0.00%
21,527	0	**18**	0	0	0	0	0.00%
4,019	0	**19**	16823	685	0	1109	78.51%
4,019	0	**20**	0	0	0	0	0.00%
4,019	0	**21**	0	0	0	0	0.00%
4,019	0	**22**	0	0	0	0	0.00%
4,019	0	**23**	0	0	0	0	0.00%
4,019	0	**24**	0	0	0	0	0.00%
4,019	0	**1**	0	0	0	0	0.00%
4,019	0	**2**	0	0	0	0	0.00%
732	0	**3**	0	2075	1212	249	17.61%
732	0	**4**	0	0	0	0	0.00%
732	0	**5**	0	0	0	0	0.00%

Figure 83: FCEV Large-SAEV Grid Demand Profile

Assuming refueling takes 6 minutes per SAEV, with negligible time for re-positioning of SAEVs during the refueling process, there would need to be 1109 refueling spaces total to support the Nice-SAEV program with these vehicles. This means that would need to be just over 3 refueling spaces per SAEV station. Despite having a larger tank than the FCEV Micro-SAEV (i.e., 5 kg vs 2.5 kg), less efficiency that the FCEV, and a longer refueling time, because the dramatically reduced number of SAEVs required, there is a net reduction in the number of refueling spaces required to support the Nice-SAEV program.

5.4 SAEV Stations and SAEV Fleets: Summary and Conclusions

Each prototype SAEV has been evaluated using the same Nice-SAEV program construct to measure fleet-centric impacts. The resulting impacts are shared below in the following table. Note that “PS” in the table below represents the number of Parking Spaces.

Table 9: Fleet-Centric Energy Impact Summary Table

SAEV Prototype	# SAEVs Required (Per Station)	# Charging /Refueling Spaces (Per Station)	VMT (%Δ VMT)	Total Energy (kWh or kg H_2)
BEV Micro-SAEV, L2	56395 (161)	24739 (71)	5,132,615 (+36.6%)	790423
BEV Micro-SAEV, L3	56395 (161)	11107 (32)	5,132,615 (+36.6%)	790423
FCEV Micro-SAEV	31,656 (90)	1716 (5)	4,946,625 (+31.4%)	51207
BEV Large-SAEV, L2	21527 (62)	17508 (50)	3,347,720 (-11.1%)	964143
BEV Large-SAEV, L3	21527 (62)	17149 (49)	3,347,720 (-11.1%)	964143
FCEV Large-SAEV	21527 (62)	1109 (3)	3,347,720 (-11.1%)	49010

For Micro-SAEV scenarios, there are distinct differences between BEV and FCEV-powertrain vehicles. The number of FCEV Micro-SAEVs required to serve the Nice-SAEV program is nearly half the number of BEV SAEVs. This is partially due to the nature of the construct (e.g., the timing of trips from CSTDM, assumptions made about fleet behavior, etc.), but also due to the longer range and downtime of the FCEVs. Note that despite the rather dramatic decrease in number of SAEVs required, the percent change in VMT from the CSTDM base case VMT is marginally different by comparison. This means that each FCEV Micro-SAEV is performing more trips per vehicle than the BEVs.

For the Large-SAEVs, the number of vehicles required remained the same for all scenarios, largely highlighting the value of having a long range for vehicles deployed in the Nice-SAEV program. This result also indicates that at a certain point, if SAEVs can serve trips for most of the day without needing a charge or refuel, then there is little difference in the number of vehicles required for the fleet regardless of the powertrain chosen. Additionally, there is a small difference between the number of spaces required for Level 2 and Level 3 BEV Large-SAEVs, indicating the relatively large influx of vehicles at the SAEV station in the afternoon could *not* be addressed within in a single hour, as the Micro-SAEVs had been.

Changes to VMT are rather minimal within Micro and Large-SAEV categories, yet when these broader categories are compared with one another, ridesharing clearly makes for significant differences between the Nice-SAEV program and the base case. Again, the Nice-SAEV program is restricted to folks who would use their LDVs to drive within their neighborhood. This analysis does not consider the effect of induced demand due to the likely attractiveness of the Nice-SAEV program, which would account for hypothetical citizens who wish to cease riding the bus, walking, biking, and so on, and thus shift other person-miles-traveled towards SAEV-VMT. If such induced demand *was* included, there would likely be an increase in VMT relative to the base case for both Micro and Large-SAEVs.

Lastly, despite far less VMT for the Large-SAEVs, there is a significant *increase* in overall energy consumed for BEVs, and a slight decrease in energy consumed for FCEVs. Starting with the BEVs, the per-mile efficiency of the Micro-SAEV is assumed to be 0.154 kWh/mile (stemming from a weighted average between High and Low-Profile Sensor efficiencies, biased towards the Low-Profile-sensor efficiency), with the Large-SAEV efficiency at nearly double with 0.288 kWh/mile. For FCEV Micro-SAEVs, the efficiency is assumed to be 96.6 miles/kg-H_2, with Large-SAEVs at a 68.3 miles/kg-H_2 efficiency. Clearly, the FCEVs took less of an efficiency decrease when upgrading in size. The energy density of each powertrain is dramatically different, with the final weight of the BEV Large-SAEV is nearly 1000 kg heavier than the FCEV.

6. Measure SAEV Impacts to Energy Grid, GHG, and CAP

The final stage of this research uses the vehicle and fleet-centric energy impacts from the preceding sections to measure the energy and environmental impacts of the Nice-SAEV program. The Holistic Energy Grid modelling tool (HiGRID) is used to measure the impacts of SAEVs on the projected California grid and grid GHG and CAP emissions. The Greenhouse Gases, Regulated Emissions, and the Energy Use in Transportation Model (GREET) is used to measure corresponding GHG and CAP impacts to the transportation sector. This section will begin with the California energy grid impacts, as measured using the HiGRID model.

6.1 Impacts of Nice-SAEV Program on California Energy Grid

The HiGRID model is a tool developed by the Advanced Power and Energy Program at the University of California, Irvine. HiGRID was created to evaluate the way that various electrical power generation technologies interact in California with a focus on measuring the opportunities and challenges of integrating renewable energy resources on the grid [184]. HiGRID is temporally resolved on an hourly basis and can be used for California cities as well as the entire state. Please refer to the flow chart diagram below for an illustration of HiGRID.

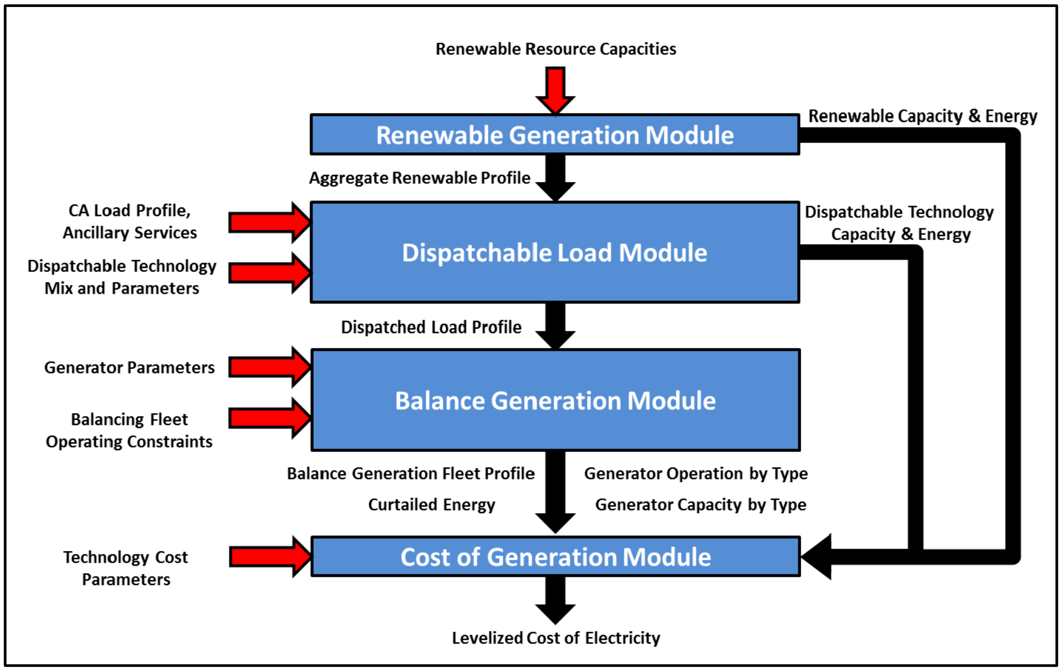


Figure 84: Flow Chart of HiGRID Model [185]

As can be seen, four modules comprise the HiGRID model. The Renewable Generation Module determines the extent to which renewable energy resources are used by taking the capacities of various renewable power generation resources as an input. The costs of these resources are used as an input for the Cost of Generation module. The Dispatchable Load Module creates a net load profile, subject to power generation resource constraints, based on hourly electricity demand and the hourly renewable energy generation available. This net load profile is created iteratively and accounts for renewable resources that may complement one another. The Balance Generation Module is the part of HiGRID that determines the exact dispatch of defined power generation resources to meet the given load profile, and the Cost of Generation Module determines the final cost of electricity, partially based on a Levelized Cost of Electricity (LCOE) model created by the California Energy Commission (CEC).

6.1.1 Nice-SAEV Program Scenario HiGRID Inputs

The renewable energy resource capacity is defined in this work to meet the anticipated 2050 Renewable Portfolio Standard (RPS) for California to reduce GHG emissions by 80% of the 1990 levels. According to a recent report by Energy and Environmental Economics, Inc. (E3), the preferred resource mix to achieve this goal is for the California electric grid to consist of the following capacities of renewable resources as shown in the Table below [186].

Table 10: California Energy Grid Resource Mix, 2050 RPS

Technology	Capacity (GW)
Rooftop PV	41.5
Solar	66
Wind	99.7
Geothermal	4.86
Hydropower	15.1

This mix of resource capacities will serve as an input into HiGRID, and depending on the load profile given, different resources will be dispatched to meet the demand. Any load above the installed capacities shown is met by load-follower and peaker natural gas power plants in HiGRID. The energy loads and the total energy required per fuel type (i.e., electricity and hydrogen) are shown below for the Micro-SAEV scenarios.

Vehicle	BEV Micro-SAEV, L2	BEV Micro-SAEV, L3	FCEV Micro-SAEV
	 BEV-SAEV	 BEV-SAEV	 FCEV-SAEV
Hour	**Daily Energy Demand %**	**Daily Energy Demand %**	**Daily Energy Demand %**
6	1.2%	1.5%	1.4%
7	0.5%	0.0%	0.0%
8	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%
10	0.0%	0.0%	0.0%
11	0.0%	0.0%	0.0%
12	0.0%	0.0%	0.0%
13	0.0%	0.0%	0.0%
14	0.0%	0.0%	0.0%
15	27.1%	54.3%	0.0%
16	27.1%	0.0%	0.0%
17	8.0%	0.0%	0.0%
18	0.0%	0.0%	0.0%
19	13.8%	28.2%	82.3%
20	4.5%	0.0%	0.0%
21	1.3%	0.0%	0.0%
22	0.0%	0.0%	0.0%
23	0.0%	0.0%	0.0%
24	6.5%	13.0%	10.7%
1	6.5%	0.0%	0.0%
2	1.9%	0.0%	0.0%
3	1.5%	3.0%	5.6%
4	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%
kWh/day	790423	790423	0
kg/day	0	0	51207
Charging rate (kw)	10	50	N/A
Initial VMT	3765392	3765392	3765392
VMT with SAEV	5132615	5132615	4946625
% Change in VMT	36.3%	36.3%	31.4%

Figure 85: Micro-SAEV Scenario HiGRID Inputs

Note the progressively shorter downtime for each SAEV design as the scenarios advance from left to right. Also note the slight difference in total VMT between the different powertrain SAEVs.

The Large-SAEV scenario inputs are shared as well in the following figure.

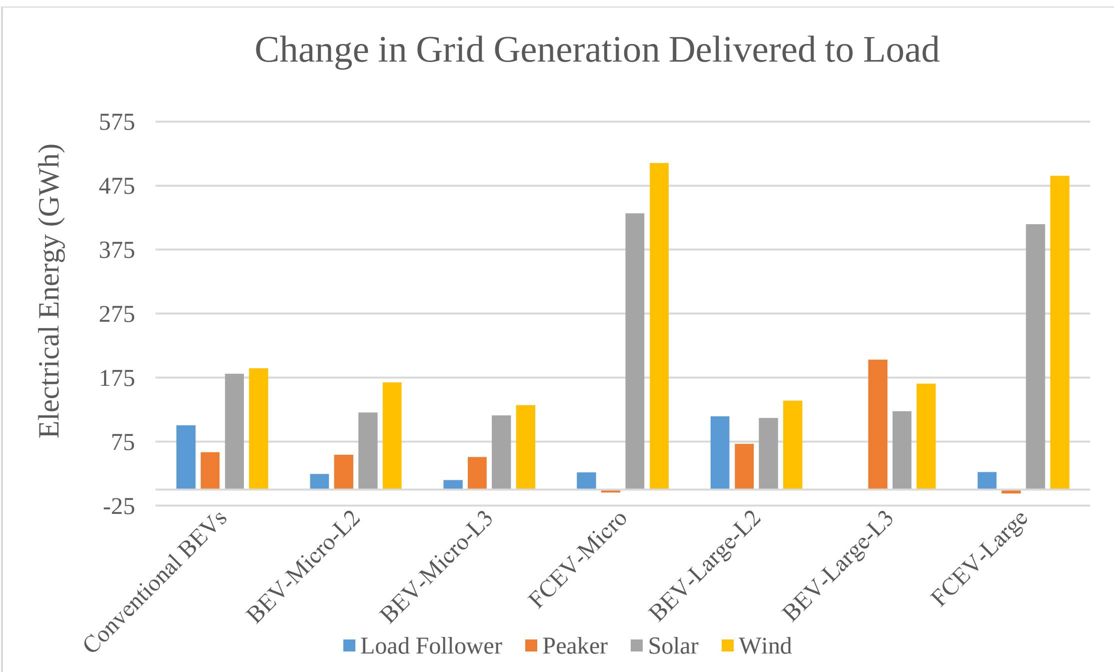
Vehicle	BEV Large-SAEV, L2	BEV Large-SAEV, L3	FCEV Large-SAEV
	 BEV-SAEV	 BEV-SAEV	 FCEV-SAEV
Hour	**Daily Energy Demand %**	**Daily Energy Demand %**	**Daily Energy Demand %**
6	2.8%	3.6%	3.9%
7	2.8%	2.7%	0.0%
8	2.5%	0.0%	0.0%
9	1.9%	0.0%	0.0%
10	1.9%	0.0%	0.0%
11	1.4%	0.0%	0.0%
12	0.0%	0.0%	0.0%
13	0.0%	0.0%	0.0%
14	0.0%	0.0%	0.0%
15	0.0%	0.0%	0.0%
16	0.0%	0.0%	0.0%
17	0.0%	0.0%	0.0%
18	0.0%	0.0%	0.0%
19	12.1%	83.8%	78.5%
20	12.1%	57.9%	0.0%
21	12.1%	0.0%	0.0%
22	12.1%	0.0%	0.0%
23	11.7%	0.0%	0.0%
24	11.6%	0.0%	0.0%
1	8.2%	0.0%	0.0%
2	0.0%	0.0%	0.0%
3	2.3%	16.1%	17.6%
4	2.3%	11.9%	0.0%
5	2.3%	0.0%	0.0%
kWh/day	964143	964143	0
kg/day	0	0	49010
Charging rate (kw)	10	50	N/A
Initial VMT	3765392	3765392	3765392
VMT with SAEV	3347720	3347720	3347720
% Change in VMT	-11.1%	-11.1%	-11.1%

Figure 86: Large-SAEV Scenario HiGRID Inputs

Relative to the Micro-SAEVs, there is a similarly decreasing downtime from left to right on the chart. However, note how there is less overall downtime for the BEV SAEVs with Level 2 protocol. For the Level 3 charging protocol and FCEV powertrain-SAEVs, there appears to be less downtime for the Large-SAEVs overall than the Micro-SAEVs.

6.1.2 Nice-SAEV Program Scenario HiGRID Energy Mix Results

The first outputs provided by the HiGRID model to discuss in this work are the changes to grid energy mix for each scenario. The energy mixes of HiGRID show the relative contribution of energy resources installed on the California grid to support the Nice-SAEV program, as the resources deploy to either provide electricity or electrolytically-sourced hydrogen, measured in GWh. Given the preceding inputs from the Nice-SAEV program, the following are the impacts to the annual electrical energy provided by the projected 2050 California electric grid resources per SAEV scenario.



While Solar and Wind resources are generally well-known, peaker-plants are often a lesser known grid resource. Contemporary peaker-plants are a relatively high-polluting resource employed in times of greatest hourly electricity demand, and grid operators generally prefer to avoid their use when possible. However, the projected 2050 peaker plants used in this analysis are cleaner than at present. Load-following is the ability of certain energy conversion resources to adjust their power output to better match grid demand. It is important to note that peaker-plants and load-following plants are both resources which contribute to increased grid GHG and CAPs, as will be shown in the following sections.

Note as well that the preceding figure includes a *Conventional BEV* case to the left, which represents a scenario where the same number of VMT are accomplished by the Nice-SAEV program but use conventionally-driven BEVs charging at the conventional timing expected for a fleet of privately-owned BEVs. This is included to provide a basis of comparison for the Nice-SAEV program, highlighting the effects not just due to being different prototypes, but also being ZEVs which interact with the California grid differently than conventional ZEVs would.

These results indicate that there is a greater potential for FCEV-powertrain vehicles to use the installed capacity of renewable energy resources than the BEV-powertrain vehicles for the scenarios presented. This is due to the timing of energy demand, where BEVs required charging during hours which did not correspond with the peak production of renewable power. FCEVs by comparison can benefit from the strategic production of hydrogen during the most economical and/or least environmentally impactful times of the day and use stored hydrogen gas whenever the SAEVs may need the fuel. As BEVs operating with an immediate changing protocol cannot transcend this requirement, the introduction of FCEVs to serve these neighborhoods results in a greater usage of renewable energy resources. Different BEV charging strategies can affect these results, as is described the Future Work section.

For the BEV cases, there is a general reduction in energy required for the Micro-SAEVs, because though they travel more VMT, the vehicles are more efficient than the BEVs projected for 2050. The BEV Large-SAEVs have more varied results, due to the relatively great overall energy required, and difference in the timing of their power demand. With Large-SAEVs charging at Level 3 mostly during the off-peak production of solar power, there is a relatively large increase in peaker-plant resources dispatched to meet this load. This would be something for grid operators to be privy to, should such a hypothetical SAEV network scale as presented in this work. For the Level 2 charging Large-SAEV, the more temporally diffuse charging demands the usage of more load-following resources. This will lead to further points of discussion in the CAP results for SO_2.

Finally, note that there is a slight *decrease* in peaker-plant and load-follower resources used for certain scenarios due to an overall load smoothing from the greater deployment of renewable resources, represented as negative values on the preceding figure.

6.1.3 Nice-SAEV Program Scenario HiGRID GHG Results

The following are the corresponding annual GHG impacts due to the Nice-SAEV program. Similar to energy grid mix results, these GHG results are annual totals and show the relative potential of the Nice-SAEV program for each of the proposed SAEV cases. California electric grid GHG emissions are measured using HiGRID, and the projected GHG emissions from the replaced conventionally-driven LDV fleet is measured using the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model (GREET). GREET is a spreadsheet-based model which estimates the full energy use and fuel-cycle emissions corresponding with a number of transportation fuels and vehicle architectures used in LDVs [190]. For this analysis, GREET is used to measure the emissions specifically from California-standard fuel production pathways.

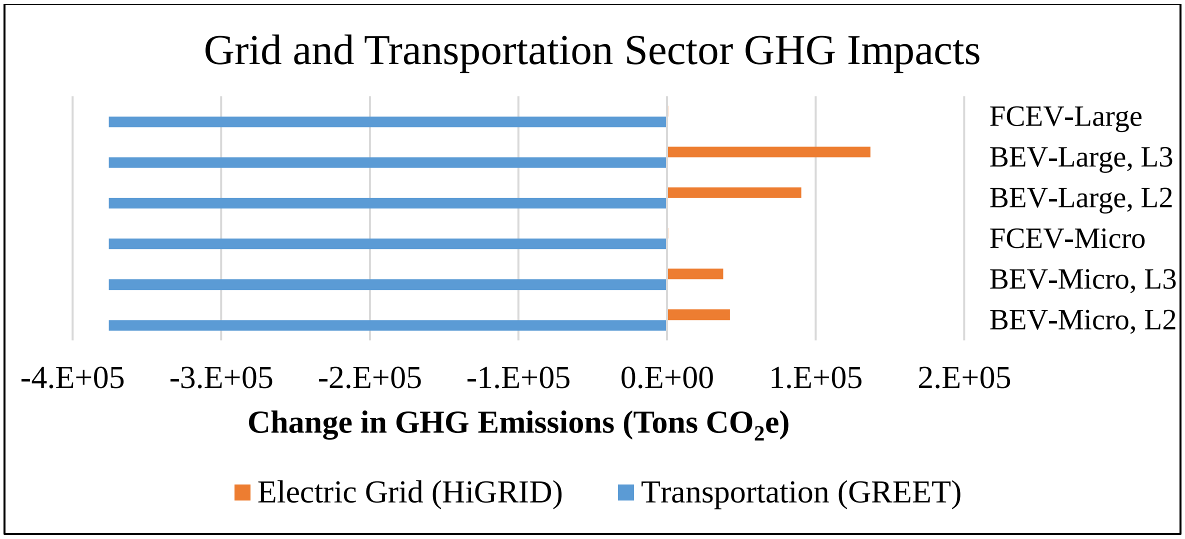


Figure 87: HiGRID GHG Results, Projected 2050 Grid and LDV Fleet vs Nice-SAEV Program

It is immediately noticeable that there is a significant positive impact for replacing the projected conventional vehicles with SAEVs for all scenarios. The total reduction in GHG from the transportation sector is significantly greater than any increase in grid-associated GHG, as measured using the GREET tool specifically for projected vehicles in California. It is important to note here that HiGRID and GREET are alike in that they both take more into account than the emissions at the vehicle "tailpipe" or power-plant "stack", with each accounting for the emissions associated with fuel supply chains as well. Also note that as of this writing, the GREET model is only able to project emissions for vehicle fleets up to the year 2040, which was used for this analysis. Because LDV GHG emissions are expected to decrease with time, a second perspective on projected emissions was garnered using the Emission Factors (EMFAC) model. Developed by and for the California Air Resources Board, EMFAC is used to estimate projected vehicular tailpipe emissions up to the year 2050. Though EMFAC gives tailpipe-only measurements, it measured a reduction of nearly 300,000 tons of CO_2 equivalent GHG emissions. For 2040, GREET estimates approximately 375,000 tons of these emissions. A reasonable estimate of the actual tailpipe *and* supply-chain emissions would therefore be between these two values. The conclusion therefore remains the same – any anticipated increases in GHG from the California grid are more than offset by the GHG reduced by replacing the projected conventionally-driven LDV fleet.

Relative to one another, the Micro-SAEVs serve the person-trip demand with the lowest GHG impact relative to the Large-SAEVs. This is despite the fact that the Large-SAEVs served the person-trips with fewer VMT. This indicates that there is a tradeoff between ridesharing capability and the overall efficiency of the vehicle. Here, it is clearly seen that despite having a significantly greater VMT due to no sharing capability, the Micro-SAEVs are generally the less GHG-impactful vehicles in the configuration presented. Next, the FCEV-SAEVs were able to have a remarkably low GHG impact relative to the BEV-SAEVs. As mentioned previously, this is a result of strategic timing of hydrogen production so as to minimize the environmental impact and cost of the fuel. There is the potential for BEV-SAEVs to benefit from other charging protocols rather than immediate, using smart charging, battery swapping, or vehicle-to-grid interaction at some point in the future as well. Such investigations are mentioned in the Future Work section towards the end of this dissertation.

Next, the grid GHG impacts of each SAEV scenario are compared to the grid GHG impacts of the conventionally-driven BEV fleet. The SAEVs compare as presented in the figure below.

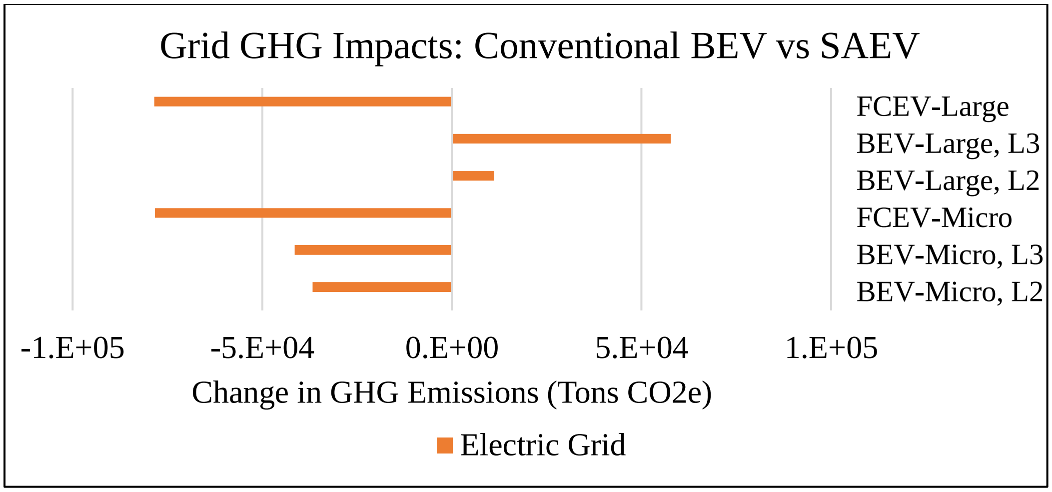


Figure 88: HiGRID GHG Results, Projected 2050 Grid and All-BEV Fleet vs Nice-SAEV Program

Recall how the Micro-SAEVs represented an increase in VMT by over 30% for all scenarios, yet, these vehicles benefit from tailored design and autonomous-technology-enhanced driving behavior and thus perform trips with a significantly higher energy efficiency. The Large-SAEVs, by comparison, are relatively inefficient, and demand a great amount of electrical energy when plugging back in. Despite the reduced VMT, these vehicles still increase the projected 2050 California energy grid GHG emissions. Worthy of note, is that the FCEV-SAEVs reduce the grid GHG emissions the most, again largely the result of strategic hydrogen production.

6.2 Impacts of Nice-SAEV Program on Criteria Air Pollutants in California

With the performance metrics of the SAEV construct defined and California energy grid results measured, the next steps are to measure the corresponding grid impacts to select CAPs of interest to serve as metrics of environmental impact. CAPs are presently defined as the following species: NO_x, SO_2, ground-level ozone, Particulate Matter (PM), CO, and lead. This study focuses on impacts to NO_x and SO_2 primarily because the energy sector currently has the most significant relative impact on these CAPs at a national scale. Additionally, the leading domestic sources of NO_x are the transportation and energy sectors, each contributing approximately 33%

of overall NO_x emissions. NO_x emissions are detrimental to environmental health both as an irritant itself, but also as a precursor to numerous hazards including smog and ground-level ozone, acid rain, and the formation of secondary PM. NOx is formed largely as a result of combustion processes, and the transition towards solar and wind power resources projected for 2050 together with and the zero-emissions SAEVs of the Nice-SAEV program together represent a combined means of reducing the top sources of NO_x.

While NO_x emissions are largely the result of a combination of transportation and energy sectors, SO_2 emissions are primarily the result of the energy sector alone at the national scale. Aside from NO_x and SO_2, the energy grid has relatively little impact on CAPs when compared to other domestic sources such as industry, agriculture, and waste processes.

To determine the environmental impacts from the various Nice-SAEV program scenarios, changes in emissions of NO_x and SO_2 are measured and compared to reference scenarios. The pollutant species are selected as a proxy for impacts on regional air quality as both are regulated under the National Ambient Air Quality Standards (NAAQS), and are well-known to have harmful human health impacts [187]–[189].

As with the measurement of GHG emissions for the replaced conventionally-driven LDV fleet, this work uses the GREET Model to measure the transportation-sector CAP impacts of the Nice-SAEV program.

6.2.1. Impacts of Nice-SAEV Program on Projected 2050 California Grid NO_x Emissions

This results section compares the relative impacts of each Nice-SAEV scenario on California NO_x emissions. Please refer to the figure below for this comparison.

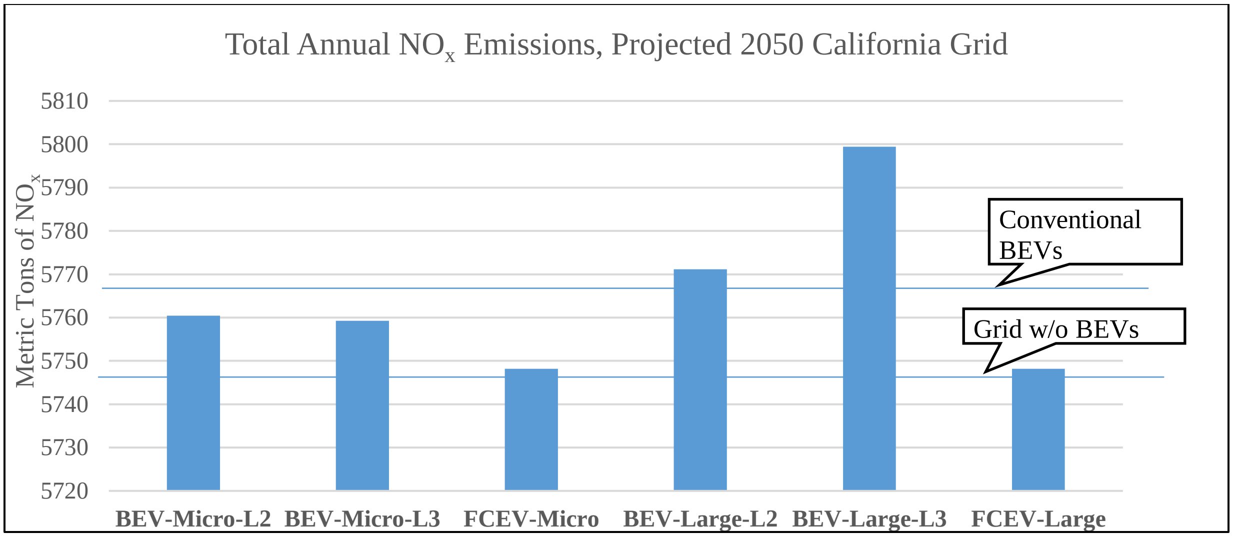


Figure 89: Total Annual NOx Emissions, Projected 2050 California Grid

Note how this chart bears resemblance to the CO_2-equivalent GHG emissions chart shown in the preceding section. A clearer view of these relative impacts to NO_x emissions is presented in the figure shown below.

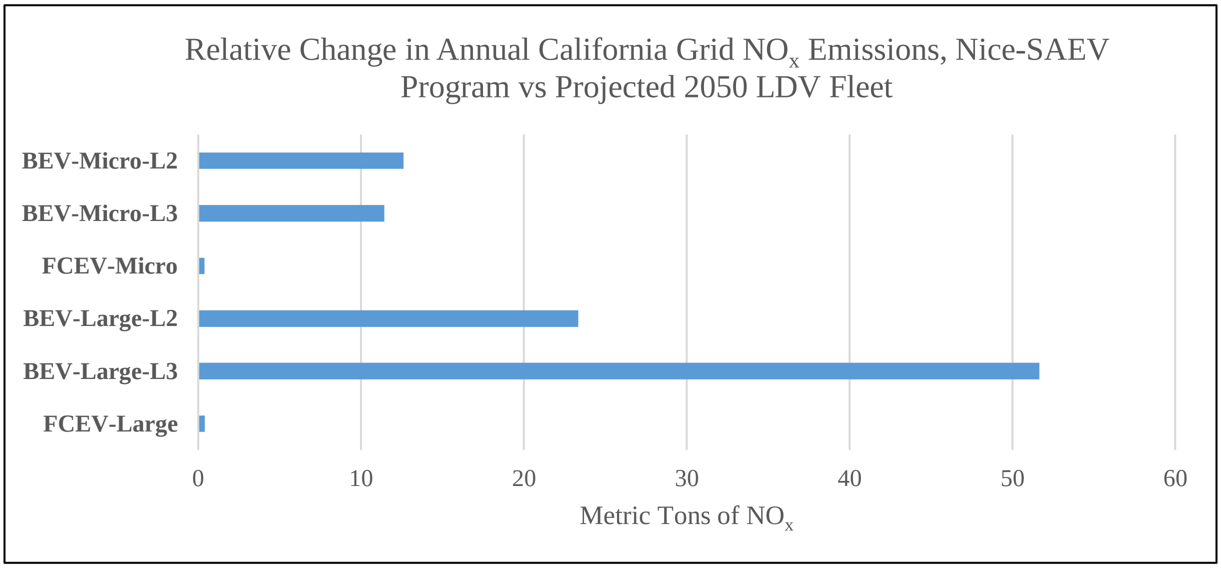


Figure 90: Relative Total Annual NO_x Emissions, Projected 2050 California Grid, SAEV Program vs Projected LDV Fleet

With this clearer perspective on the impact of the Nice-SAEV program on 2050 California grid NO_x emissions, one can see a similar relatively minor impact caused by the additional

FCEVs in the network. Note that the GREET results for the transportation sector emissions were not included on this chart. The NO_x emissions reduced by replacing the conventionally-driven LDV fleet is measured at 290.9 metric tons, far offsetting the increase in NO_x on the grid side of the Nice-SAEV program, and once again highlighting the relative environmental importance of incorporating SAEVs on California roadways. As another perspective, the Nice-SAEV program impacts relative to an all-BEV scenario are found below.

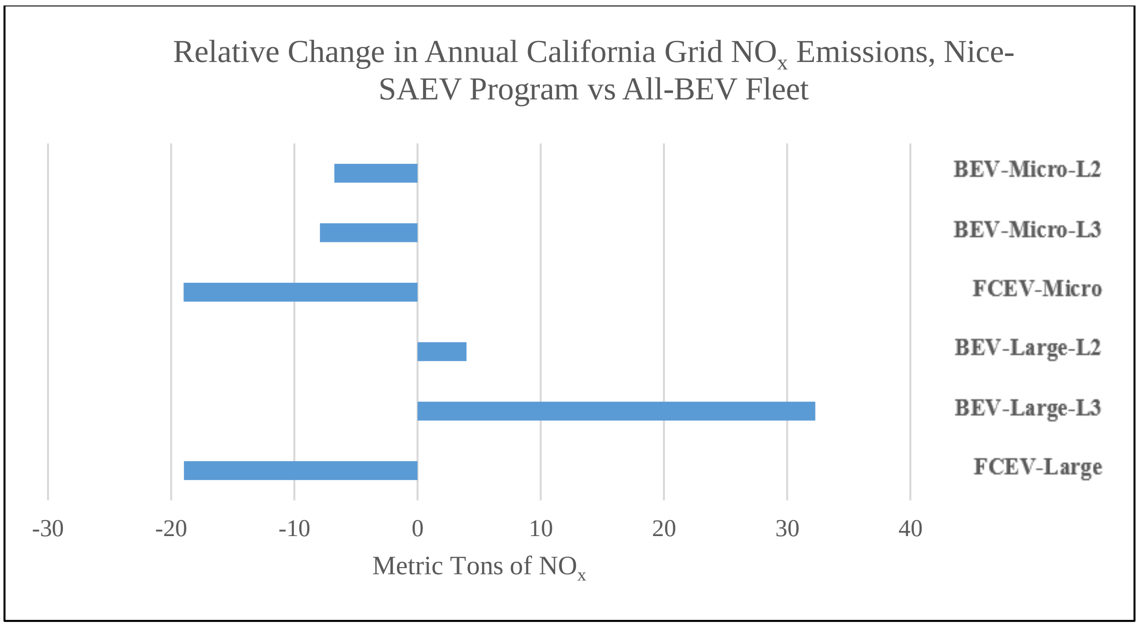


Figure 91: Relative Change in Annual California Grid NOx Emissions, Nice-SAEV Program vs All-BEV Fleet

Note that the NO_x emissions again track well with the CO_2-equivalent GHG emissions previously shared.

6.2.2. Impacts of Nice-SAEV Program on SO_2 Emissions

Sulfur is added to natural gas as an odorant to provide a people with an indication that there may be a hazardous leak nearby. While helpful for general safety, the SO_2 gas formed predominantly by the energy sector poses great risks to human and ecological health in increased rates of asthma, increased formation of PM, and damage to local flora. While NO_x emissions are presently the result of mostly the energy and transportation sectors together, SO_2 emissions are mostly the result of the energy sector alone. It is important to note that while NO_x appeared to be affected proportional to the GHG impacts shared, not all CAPs are affected proportionally to the CO_2-equivalent GHG emissions discussed. Please refer to the figure below for an illustration of the annual emissions of SO_2 from the projected California energy grid.

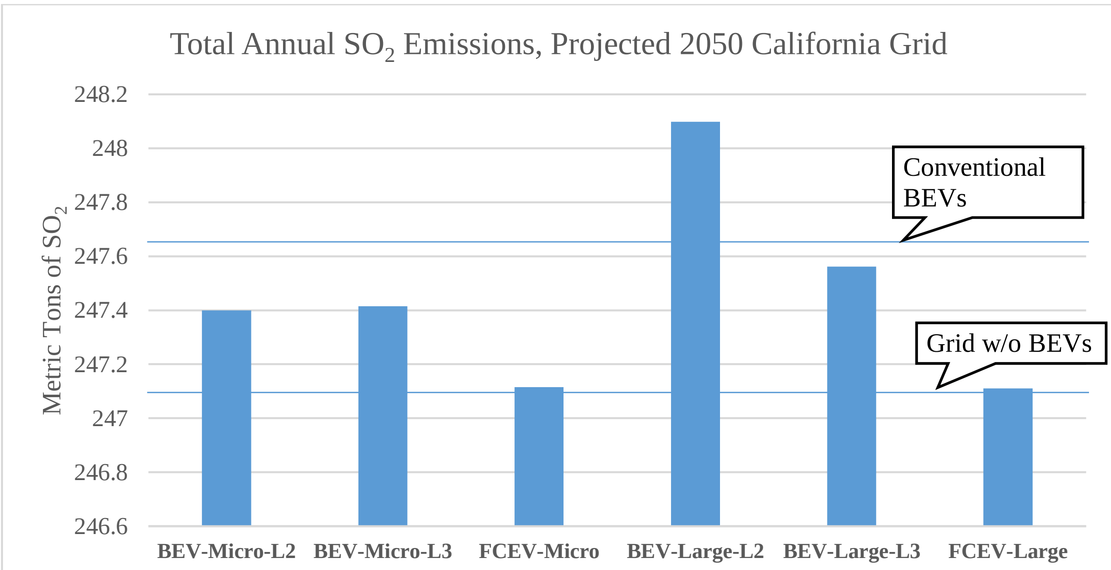


Figure 92: Total Annual SO_2 Emissions, Projected 2050 California Grid

While most scenarios have similarities to both the GHG and NO_x results, the relative impact of Level 2 and Level 3-charging BEV Large-SAEVs have inverted from the past scenarios. The results of the energy mix used may help indicate why, as there *is* a different dispatch of resources from the Level 2 and Level 3 scenarios. Specifically, the Level 3 BEV Large-SAEV scenario rely on an increased dispatch of peaker-plants, whereas the Level-2 BEV Large-SAEV scenario results in a partial mix between peaker-plants and load-following for the extra electrical energy. It is worthy to note that all combustion for this grid mix is assumed to use natural gas as fuel, regardless of technology, though HiGRID uses emissions factors which correspond to greater SO_2 emissions from load-following plants, relative to peaker-plants.

Please refer to the figure below for a comparison of the SO_2 emissions resulting from the Nice-SAEV program relative to the projected 2050 LDV fleet.

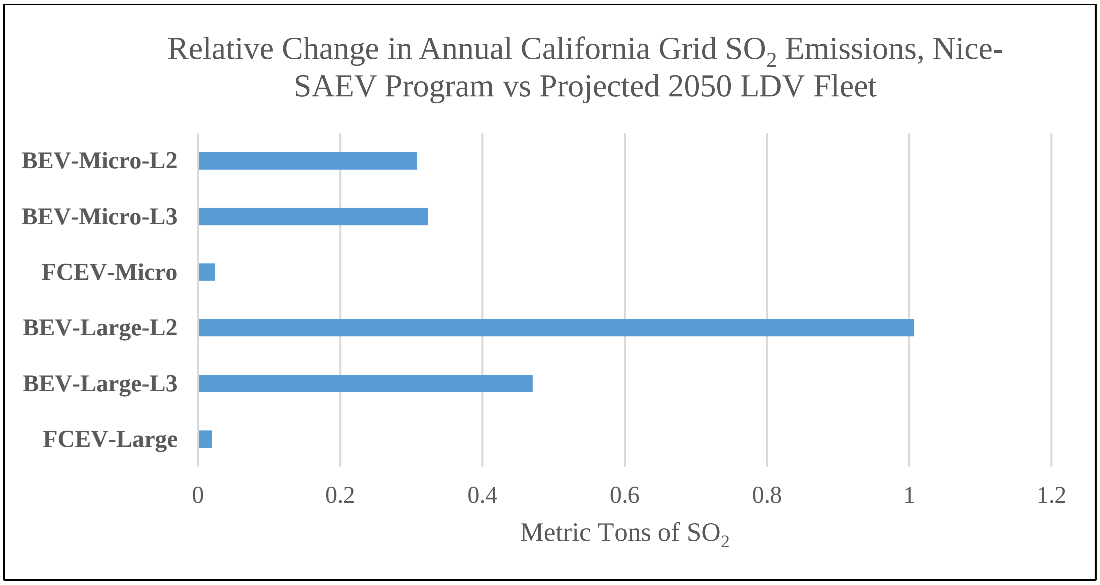


Figure 93: Relative Change in Annual California Grid SO_2 Emissions, Nice-SAEV Program vs Projected 2050 LDV Fleet

The clearer perspective on the above scenario helps to see that, the relative SO_2 emissions for Level 2 and Level 3 BEV Large-SAEVs are about proportional-and-opposite to the NO_x emissions. Where Level 3 NO_x emissions were about double those of Level 2 for this relative comparison, now the SO_2 emissions are doubled by operating the Nice-SAEV program with a Level 2 charging protocol. This is because the Level 2 and Level 3 BEV Large-SAEVs charge using *different grid resources*, as presented in the energy grid mix results. For Large-SAEVs charging at Level 2, there is a greater dependence on load followers than for the Level 3. This means that the load following grid resources are projected to emit more SO_2 than the peaker plants. Again, the GREET results indicate a wide offset of grid emissions by the reductions from the projected transportation-sector emissions, with GREET measuring transportation-sector SO_2-emissions reduced at 75.7 metric tons.

The final comparison of California grid SO_2 emissions for the Nice-SAEV program is relative to an all-BEV scenario, as shown in the figure below.

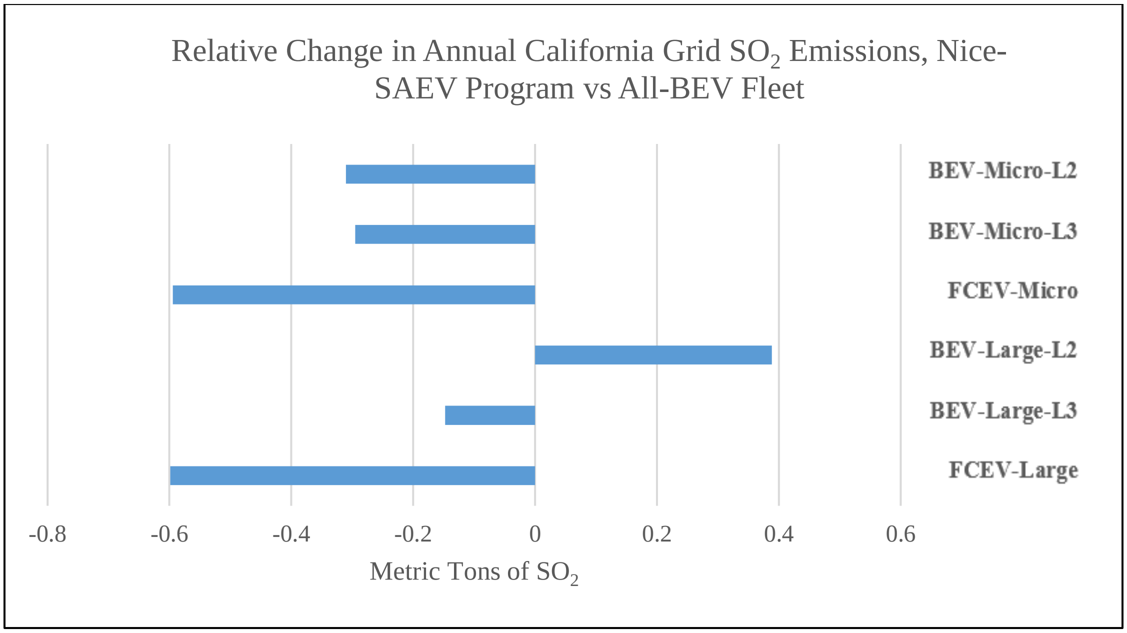


Figure 94: Relative Change in Annual California Grid SO_2 Emissions, Nice-SAEV Program vs All-BEV Fleet

With this closer perspective, the Nice-SAEV program is clear to have a more positive relative impact to SO_2 emissions than to the NO_x emissions when compared to an all-BEV future scenario. Specifically, where both BEV Large-SAEVs increased NO_x emissions before, just one BEV Large-SAEV increased SO_2 emissions. Overall, this is just one scenario where the Nice-SAEV program was *not* an improvement to an otherwise entirely-ZEV future from a grid-centric perspective.

6.3 Energy Grid GHG and CAP Impacts Summary

The widest range of prototype SAEVs have been evaluated for their effect on the California energy grid GHG and CAP impacts to help illustrate the relative impacts of these vehicles as part of a hypothetical deployment construct. Vehicle sharing, in the sense of pooled-rides, is a key to transportation sustainability. Yet, relative to high-efficiency single-occupancy Micro-SAEVs, there was an overall increase in energy consumed for some of the Large-SAEV prototypes shared, thus affirming the importance of vehicle efficiency in the overall network. Such result represents a tradeoff between the efficiency of the overall fleet in allocating rides (e.g., with VMT serving as the metric for allocation efficiency) and the efficiency of the individual SAEVs themselves. The tradeoff between vehicle and fleet-centric efficiency highlights a superseding theme of this work, that vehicle-centric and fleet-centric energy impacts must be considered in tandem to garner a full understanding of SAEV-network performance.

In terms of environmental impacts, the GHG and CAP impacts of the Nice-SAEV program to the projected California energy grid were minimal for the FCEV-powertrain prototypes shared. However, the deployment of all SAEV prototypes resulted in a substantial overall net reduction in GHG and both CAPs due to the replacement of the projected conventionally-driven LDV fleet with SAEVs in the transportation sector. Such results indicate the relative importance of each of these sectors in their potential for alleviating environmental damage through the adoption of SAEV technologies.

7. Conclusions

7.1 Vehicle-Centric Energy Impact Conclusions

- **Installing SAV technology (e.g., communications equipment, cameras, radar, etc.) increases electrical power consumption, weight, and potentially the aerodynamic drag of the vehicle. Of these factors, electrical power consumption by far has the greatest negative impact on efficiency.**

  Installing and operating SAV technology without garnering the benefits of eco-driving and platooning can reduce overall vehicular energy efficiency by 5-10%. Approximately 70-80% of this decrease is due to the additional power consumption of the SAV equipment. Put in context, the power consumption of the most power-intensive SAV technologies is similar to a contemporary air conditioning compressor, which negatively affects efficiency on a similar scale. In the future, efficient on-board computers and sensors should reduce the power consumption. Future efforts to refine the calculation of *CdA* using wind tunnel testing or CFD simulation could alter this relative importance.

- **Eco-driving *and* platooning for "Large-Sensor"-equipped vehicles are required to mitigate the efficiency decrease associated with the addition of sensors.**

  The energy consumption of SAV technology is significant, as are the efficiency improvements that such technologies can facilitate. However, if a vehicle is outfitted with a relatively large and energy intensive set of sensors that support 250m-or-less range of communications for eco-driving behavior and provide a 10% reduction in drag from platooning, the overall impact on efficiency just breaks even or becomes slightly *negative.* The threshold for such vehicles is typically a 350m range of V2I together with a 20% reduction in drag. While energy is a primary focus of this work, it is worthy to note that the benefits of this SAEV network are still likely strong with improved safety, convenience, affordability, and greater access.

- **V2I-enabled variable speed limit messages offered diminishing returns on efficiency improvement when communication range exceeded 350m.**

  V2I range was tested in 250m, 350m, and 450m increments. While a significant improvement was measured between 250m and 350m (typically doubling the efficiency improvement), the 350m to 450m increment often resulted in just a slight efficiency improvement (typically just one or two percent improvement). Therefore, should planners choose to implement V2I systems to help improve vehicular energy efficiency via advanced notice of upcoming red-lights or similar speed oscillations, and have the choice of operating range, the standard-to-long-range V2I communications devices are adequate for near maximum efficiency improvement. Planners should note however, that while the efficiency improvement may be diminishing, important messages relating to safety may still be valuable with more advanced notice.

- **V2V-enabled platooning offers progressively improving efficiency as drag decreases.**

  To the extent safe, individual vehicles participating in V2V-enabled platoons should be positioned in the closest proximity to one another. While a range of potential drag reductions was tested and discussed, future research efforts would be prudent to identify the extent to which drag can be reduced via the platooning of vehicles of various frontal area, drag coefficient, and so on. Note that the preceding definition of platooning does not consider another potential scenario involving non-connected vehicles, where the lead-vehicle of a platoon could use non-communications-based sensors (e.g., radar, cameras, LiDAR, etc.) to safely, closely follow a nearby non-connected vehicle. Such situation may be possible and would further reduce average aerodynamic drag of the platoon if employed.

7.2 Fleet-Centric Energy Impact Conclusions

- **FCEV-powered SAEVs can accomplish the same level of service with 16-28% fewer vehicles**

  SAEV-fleet sizes depend greatly on the range and minimal downtime (e.g., due to refueling/recharging). Assuming similar performance to present day vehicles, FCEVs have a significant advantage. BEVs may benefit from battery-swap capability, and future work can cover a comparison between these and other potential technologies.

- **The first SAEV stations in California, if sited based on proximity to intrazonal activity and public transit stations, should be constructed starting in Los Angeles County.**

  The first 10 SAEV stations sited for the validated 2010 scenario include 8 in Los Angeles County, with 4 of the 10 in Los Angeles County for the 2050 scenario, both times representing the most stations in any single county. Such would be pertinent information should policymakers wish to investigate locations with the most potential for an actual Nice-SAEV deployment.

7.3 Energy and Environmental Impact Conclusions

- **Environmental impacts depend largely on the overall energy efficiency of the individual SAEV**

  Though the Fleet-Centric energy impacts showed a reduction in VMT for shared vehicles, the sharing of relatively *inefficient* vehicles was measured to have a worse overall energy consumption than the highly-efficient single-occupancy Micro-SAEVs for the BEV powertrain. The benefits of ridesharing are still evident and valuable, it is just important to consider that there are tradeoffs when designing such a SAEV network. Future efforts could consider the middle-ground of somewhat efficient, yet shareable, SAEVs such as the Medium-SAEV prototypes presented in this work. Furthermore, policymakers may want to consider incentives or other regulatory measures as written into upcoming environmental legislation to ensure that both efficient *and* sharable SAEVs are used.

- **There are energy and environmental advantages for SAEVs with the ability to charge or refuel at strategic times.**

  The scenarios presented for this work highlight the differences between FCEVs and BEVs using immediate charging protocols. Because the hydrogen for FCEVs can be produced and stored at separate times from vehicle demand, the production of hydrogen can be timed at least cost and/or environmental impact. For immediate charging BEVs, there is no temporal separation between the time they need to charge and the time that electrical power must be provided. The resulting impacts to energy grid mixes employed, GHG emissions, and CAPs are shown to be significant.

7.4 Future Work

- **Determine the optimal eco-driving strategies for each prototype SAEV**

  While this work demonstrates the potential for FETCH, future studies could use FETCH to determine the best acceleration and deceleration profiles for each specific vehicle, rather than the same profile for each vehicle. While a valuable basis for comparison and preferred for the scope of this work, the future potential for FETCH to be a platform for numerous tests is demonstrated as well, especially in the vehicle-design context.

- **Measure total *CdA* per SAEV prototype using computational fluid dynamics (CFD) software or wind tunnel testing.**

The *CdA* of the high-profile SAEV sensor installation was estimated by adding the *CdA* of the base vehicle with the *CdA* of the high-profile sensor package. Future studies could improve the accuracy of this estimation by empirically measuring the *CdA* of such sensor-equipped vehicles using wind-tunnel testing or using CFD software.

- **Determine the optimal platooning distance for each SAEV using CFD or wind-tunnel testing, and measure the corresponding reductions in aerodynamic drag**

  Again, within the scope of this work, the use of an easily compared metric for all different SAEV architectures is preferred. However, future work could hone these parameters and determine under what conditions each SAEV would best perform in a platoon (either mixed-vehicle, or same-vehicle), and measure the resulting aerodynamic drag.

- **Determine the optimal eco-driving profiles for each prototype SAEV**

  While this work demonstrates an example deceleration profile for use in the range of eco-driving scenarios, another natural extension of this work would be to explore the potential for each prototype to have an optimal deceleration profile based on specific vehicle characteristics.

- **V2I communication validation using Hardware-in-Loop (HIL)-equipment, or validation using real-world testing**

  The additional validation of V2I communication using HIL simulation, or real-world testing would be an appropriate next step for this work. The Horiba Institute for Mobility and Connectivity (HIMaC) is expected to fill this niche at UC Irvine in the near future.

- **Optimize Dispatch of the Nice-SAEV Vehicle Fleets**

  The fleet allocation strategy employed for the hypothetical scenarios provide reasonable use cases and corresponding temporal energy demands, and future research efforts could explore optimization tools and strategies for allocating fleet vehicles to further minimize the vehicles required for individual deployments. For example, the current fleet deployment strategy is shared for all vehicle types where a large, single fleet of vehicles is deployed to meet an hourly demand. It could be possible that sending several fleets in a staggered deployment (i.e., one every two hours), could help prevent this large fleet of vehicles all returning to the SAEV-Station at once and *after* peak solar power generation. While such as optimization may be focused on reducing the number of fleet vehicles, an optimization may also be developed for the purpose of minimizing grid emissions by maximizing the number of SAEVs charging in the middle of the day. There may be a tradeoff for intrazonal trips here, as there is a peak of person-trips during peak solar generation. However, should the Nice-SAEV program expand and serve more-work-based trips, the overall fleet would have some relative down-time between the morning and evening travel demand peaks.

- **Expand the Nice-SAEV program**

  The Nice-SAEV program is a feasible example for the SAEV future, and should the proposed program expand into adjacent neighborhoods and beyond, a greater number of people would be able to use the shared vehicles. The CSTDM dataset used for this work has all trips under 100 miles long, would could ultimately encompass the vast majority of LDV trips within California. While there are truly unlimited configurations for such a shared deployment, expanding the program to serve inter-neighborhood trips in addition to the present intra-neighborhood trips would illustrate further potential for SAEVs at larger scale deployment.

  Such efforts to expand the Nice-SAEV program could also consider the potential effects of induced demand by shifting various other modes of transit into the Nice-SAEV program, such as Walking, Biking, Busing, or others. Because the CSTDM is projected for 2050 and has the trip modes anticipated, the analysis could leverage the work of researchers who have already estimated the mode-shifts for communities with autonomous vehicle systems. Such potential research avenues would increase the VMT served by the Nice-SAEV program, and thus correspond to increased load on the California energy grid for which to explore further opportunities and challenges.

- **Explore Battery-Swap capability for BEV scenarios**

  Of the many future possibilities for BEV fleets, battery swap technology may become a way to reduce vehicle downtime while also mitigating the battery degradation caused by fast charging batteries with contemporary chemistry.

- **Measure potential for Vehicle-to-Grid (V2G) charging and Smart Charging of BEV-SAEV fleets**

  V2G charging is a potential opportunity for BEVs and the local electric grid to strategize charging and discharging such that a BEV fleet can support the energy grid with energy storage and ancillary services. While not in the scope of this work, the HiGRID model is capable of such simulation scenarios and future studies could provide an interesting insight into the added value SAEV fleets could have for the California electric grid. Similarly, exploring the role of smart charging, which is the strategic timing and power delivery of electricity to BEVs, could be of interest to future researchers.

- **Translation of this work into potential socio-political impacts**

  Further exploration into the potentially *negative* socio-political impacts of the SAEV future would provide a greater context for community leaders and policymakers to preemptively plan for unforeseen threats to livelihoods and environmental justice.

REFERENCES

[1] National Highway Traffic Safety Administration, “Motor Vehicle Traffic Crashes as a Leading Cause of Death in the United States, 2015,” no. February 2018, p. 5, 2018.

[2] National Highway Traffic Safety Administration., “Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey,” no. February, pp. 2–3, 2015.

[3] National Highway Traffic Safety Adminstriation, “2016 Fatal Motor Vehicle Crashes: Overview,” no. October, pp. 1–9, 2017.

[4] California Air Resources Board, “Assessment of a Zero Emission Vehicle Requirement for Light and Heavy-Duty Vehicle Fleets: Public Workshop--August 30, 2018,” *Calif. Air Resour. Board*, 2018.

[5] T. D. Chen, K. M. Kockelman, and J. P. Hanna, “Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions,” *Transp. Res. Part A*, vol. 94, pp. 243–254, 2016.

[6] Benjamin Allen, “SB-59 Autonomous vehicle technology: Statewide policy,” 2018.

[7] P. M. Bosch, F. Becker, H. Becker, and K. W. Axhausen, “Cost-based analysis of autonomous mobility services,” 2018.

[8] B. Schoettle and M. Sivak, “Potential Impacts of AV Household Usage,” no. February, 2015.

[9] C. J. Haboucha, R. Ishaq, and Y. Shiftan, “User preferences regarding autonomous vehicles,” *Transp. Res. Part C Emerg. Technol.*, vol. 78, pp. 37–49, 2017.

[10] D. Sperling and A. Brown, “Three Revolutions: Steering Automated, Shared, and Electric Vehicles to a Better Future,” *Washington, DC Isl. Press*, 2018.

[11] U.S. Energy Information Administration, *Monthly Energy Review, May 2019*. 2019.

[12] US EPA, “Fast Facts: U.S. Transportation Sector Greenhouse Gas Emissions, 1990 – 2017,” no. June, 2019.

[13] United States Environmental Protection Agency, “The 2018 EPA Automotive Trends Report,” no. March, 2019.

[14] US Energy Information Administration, “Annual Energy Outlook 2016, with Projections to 2040,” 2016.

[15] USDoT, “State Motor Vehicle Registrations, 2017,” 2019.

[16] California Energy Commission, “Tracking Progress: Zero-Emission Vehicles and Infrastructure,” no. January, 2018.

[17] “Electric Vehicle Charging Infrastructure: Multifamily Building Standards, Carb Technical and Cost Analysis: 2019,” 2018.

[18] Waymo, “Waymo Disengagement Report.” 2018.

[19] USDoT, “Average Annual Miles per Driver by Age Group,” 2018.

[20] V. Wifvat, “A Planning Tool to Assess Advanced Vehicle Sensor Technologies on Traffic Flow, Fuel Economy, and Emissions,” University of California, Irvine, 2016.

[21] User: Dllu, “Waymo Chrysler Pacifica Hybrid undergoing testing in the San Francisco Bay Area,” 2019.

[22] Creative Commons, “Attribution-ShareAlike 4.0 International (CC BY-SA 4.0),” 2019. .

[23] M. Bertozzi, A. Broggi, and A. Fascioli, “Vision-based intelligent vehicles: State of the art and perspectives,” *Rob. Auton. Syst.*, vol. 32, no. 1, pp. 1–16, Jul. 2000.

[24] M. Bertozzi, A. Broggi, M. Cellario, A. Fascioli, P. Lombardi, and M. Porta, “Artificial vision in road vehicles,” *Proc. IEEE*, vol. 90, no. 7, pp. 1258–1271, Jul. 2002.

[25] D. J. LeBlanc *et al.*, “CAPC: A road-departure prevention system,” *IEEE Control Syst. Mag.*, vol. 16, no. 6, pp. 61–71, 1996.

[26] Z. Sun, G. Bebis, and R. Miller, “On-road vehicle detection: a review.,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 5, pp. 694–711, May 2006.

[27] J. Janai, A. Behl, and A. Geiger, “Computer Vision for Autonomous Vehicles: Problems, Datasets and State-of-the-Art,” *ISPRS J. Photogramm. Remote Sens.*, 2017.

[28] D. Kissinger, “Millimeter-Wave Receiver Concepts for 77 GHz Automotive Radar in Silicon-Germanium Technology,” 2012.

[29] J. D. Turner and L. Austin, “Sensors for automotive telematics,” *Meas. Sci. Technol.*, vol. 11, no. 2, pp. R58–R79, Feb. 2000.

[30] W. Zhang, “LIDAR-based road and road-edge detection,” *IEEE Intell. Veh. Symp. Proc.*, pp. 845–848, 2010.

[31] K. Kidono, T. Miyasaka, A. Watanabe, T. Naito, and J. Miura, “Pedestrian recognition using high-definition LIDAR,” *IEEE Intell. Veh. Symp. Proc.*, no. Iv, pp. 405–410, 2011.

[32] Y. Wang, W.-L. Chao, D. Garg, B. Hariharan, M. Campbell, and K. Q. Weinberger, “Pseudo-LiDAR from Visual Depth Estimation: Bridging the Gap in 3D Object Detection for Autonomous Driving,” 2018.

[33] A. Carullo, M. Parvis, and S. Member, “An Ultrasonic Sensor for Distance Measurement in Automotive Applications,” *Sensors (Peterborough, NH)*, vol. 1, no. 2, pp. 143–147, 2001.

[34] NHTSA, “Vehicle-To- Vehicle Communications: Readiness Of V2V Technology For Application,” pp. 1–4, 2014.

[35] V. Wifvat, B. Shaffer, and S. Samuelsen, “A Planning Tool to Assess Advanced Vehicle Sensor Technologies on Traffic Flow, Fuel Economy, and Emissions,” in *SAE Technical Paper Series*, 2018, vol. 1.

[36] S. E. Shladover and X. Lu, “Using Cooperative Adaptive Cruise Control (CACC) to Form High-Performance Vehicle Streams Definitions , Literature Review and Operational Concept Alternatives,” no. June, 2014.

[37] D. Lang, T. Stanger, and L. del Re, “Opportunities on Fuel Economy Utilizing V2V Based Drive Systems,” Apr. 2013.

[38] Arash Olia, G. W., and S. N. Razavi, "Microsimulation based Impact Assessment of the Vehicle to Vehicle (V2V) System for Work Zone Safety," *CSCE 2013 Gen. Conf.*, no. June, pp. 0–10, 2013.

[39] M. Fountoulakis, N. Bekiaris-Liberis, C. Roncoli, I. Papamichail, and M. Papageorgiou, "Highway traffic state estimation with mixed connected and conventional vehicles: Microscopic simulation-based testing," *Transp. Res. Part C Emerg. Technol.*, vol. 78, pp. 13–33, 2017.

[40] H. Yang and W. L. Jin, "A control theoretic formulation ofgreen driving strategies based on inter-vehicle communications," *Transp. Res. Part C Emerg. Technol.*, vol. 41, pp. 48–60, 2014.

[41] S. Shladover and J. Misener, "Investigating the Potential Benefits of Broadcasted Signal Phase and Timing (SPAT) Data under IntelliDrive - Task 2: Identification of Use Cases SPAT Data," pp. 1–13, 2010.

[42] M. Wang, W. Daamen, S. P. Hoogendoorn, and B. van Arem, "Connected variable speed limits control and car-following control with vehicle-infrastructure communication to resolve stop-and-go waves," *J. Intell. Transp. Syst. Technol. Planning, Oper.*, vol. 20, no. 6, pp. 559–572, 2016.

[43] B. Asadi and A. Vahidi, "Predictive Cruise Control: Utilizing Upcoming Traffic Signal Information for Improving Fuel Economy and Reducing Trip Time," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 3, pp. 707–714, May 2011.

[44] D. Hibberd *et al.*, "Ecodriver. D12.2: Multi-modal in-vehicle and nomadic device eco-driving support for car drivers," 2014.

[45] C. C. Chan, "The state of the art of electric, hybrid, and fuel cell vehicles," *Proc. IEEE*, vol. 95, no. 4, pp. 704–718, 2007.

[46] A. Khaligh and Z. Li, "Battery, ultracapacitor, fuel cell, and hybrid energy storage systems for electric, hybrid electric, fuel cell, and plug-in hybrid electric vehicles: State of the art," *IEEE Trans. Veh. Technol.*, vol. 59, no. 6, pp. 2806–2814, 2010.

[47] G. L. Hunt, "Great battery search," *IEEE Spectr.*, vol. 35, no. 11, pp. 21–28, 1998.

[48] Dominic A. Notter *et al.*, "Contribution of Li-ion batteries to the environmental impact of electric vehicles," *Environ. Sci. Technol.*, vol. 44, no. 19, p. 43, 2010.

[49] D. Reichmuth, "New Data Show Electric Vehicles Continue to Get Cleaner," *Union of Concerned Scientists*, 2018. [Online]. Available: https://blog.ucsusa.org/dave-reichmuth/new-data-show-electric-vehicles-continue-to-get-cleaner. [Accessed: 24-Jun-2019].

[50] California Air Resources Board, "2018 Annual Evaluation of Fuel Cell Electric Vehicle Deployment & Hydrogen Fuel Station Network Development," 2018.

[51] US Department of Energy, "Hydrogen Production: Natural Gas Reforming How Does It Work?," 2019. [Online]. Available: https://www.energy.gov/eere/fuelcells/hydrogen-production-natural-gas-reforming.

[52] US Department of Energy, "Hydrogen Production: Natural Gas Reforming How Does It

Work?," 2019. .

[53] N. A. Kelly, T. L. Gibson, and D. B. Ouwerkerk, "A solar-powered, high-efficiency hydrogen fueling system using high-pressure electrolysis of water: Design and initial results," *Int. J. Hydrogen Energy*, vol. 33, no. 11, pp. 2747–2764, 2008.

[54] P. P. Edwards, V. L. Kuznetsov, W. I. F. David, and N. P. Brandon, "Hydrogen and fuel cells: Towards a sustainable energy future," *Energy Policy*, vol. 36, no. 12, pp. 4356–4362, 2008.

[55] California Air Resources Board, "2018 Annual Evaluation of Fuel Cell Electric Vehicle Deployment & Hydrogen Fuel Station Network Development," 2018.

[56] B. Loeb, K. M. Kockelman, and J. Liu, "Shared autonomous electric vehicle (SAEV) operations across the Austin, Texas network with charging infrastructure decisions," *Transp. Res. Part C Emerg. Technol.*, vol. 89, no. January, pp. 222–233, 2018.

[57] G. S. Bauer, J. B. Greenblatt, and B. F. Gerke, "Cost, Energy, and Environmental Impact of Automated Electric Taxi Fleets in Manhattan," *Environ. Sci. Technol.*, vol. 52, no. 8, pp. 4920–4928, 2018.

[58] S. Shaheen and N. Chan, "Mobility and the Sharing Economy: Potential to Overcome First- and Last-Mile Public Transit Connections," *UC Berkeley Transp. Sustain. Res. Cent.*, pp. 573–588, 2016.

[59] J. Alonso-mora *et al.*, "On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment," *Proc. Natl. Acad. Sci.*, vol. 115, no. 3, pp. E555–E555, 2018.

[60] T. S. Stephens, J. Gonder, Y. Chen, Z. Lin, C. Liu, and D. Gohlke, "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles," 2016.

[61] C. Stiller, F. Puente León, and M. Kruse, "Information fusion for automotive applications – An overview," *Inf. Fusion*, vol. 12, no. 4, pp. 244–252, Oct. 2011.

[62] M. Harb, Y. Xiao, G. Circella, P. L. Mokhtarian, and J. L. Walker, "Projecting Travelers into a World of Self-Driving Vehicles: Estimating Travel Behavior Implications via a Naturalistic Experiment," pp. 1–17, 2018.

[63] A. Pernestål and I. Kristoffersson, "Effects of driverless vehicles – Comparing simulations to get a broader picture," *Eur. J. Transp. Infrastruct. Res.*, vol. 19, no. 1, pp. 1–23, 2019.

[64] US Energy Information Administration, "How Electricity Is Delivered To Consumers," 2018. [Online]. Available: https://www.eia.gov/energyexplained/index.php?page=electricity_delivery.

[65] California Energy Commission, "Electric Generation Capacity & Energy," 2019. [Online]. Available: https://ww2.energy.ca.gov/almanac/electricity_data/electric_generation_capacity.html.

[66] California State Senate, *Senate Bill 100: California Renewables Portfolio Standard Program*, no. 1266. 2015, pp. 2013–2016.

[67] H. Ibrahim, A. Ilinca, and J. Perron, "Energy storage systems-Characteristics and comparisons," *Renew. Sustain. Energy Rev.*, vol. 12, no. 5, pp. 1221–1250, 2008.

[68] B. Tarroja, L. Zhang, V. Wifvat, B. Shaffer, and S. Samuelsen, “Assessing the stationary energy storage equivalency of vehicle-to-grid charging battery electric vehicles,” *Energy*, vol. 106, pp. 673–690, 2016.

[69] P. Denholm, M. O’Connell, G. Brinkman, and J. Jorgenson, “Overgeneration from Solar Energy in California. A Field Guide to the Duck Chart,” 2015.

[70] US Energy Information Administration, “Hydrogen for refineries is increasingly provided by industrial suppliers,” *U.S. Energy Information Administration website*, 2016. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=24612#.

[71] United States Department of Energy, “Hydrogen Production: Central versus Distributed Production,” 2019. [Online]. Available: https://www.energy.gov/eere/fuelcells/central-versus-distributed-hydrogen-production.

[72] T. D. Chen, K. M. Kockelman, and J. P. Hanna, “Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions,” *Transp. Res. Part A Policy Pract.*, vol. 94, pp. 243–254, 2016.

[73] N. Z. Muradov and T. N. Veziroğlu, “‘Green’ path from fossil-based to hydrogen economy: An overview of carbon-neutral technologies,” *Int. J. Hydrogen Energy*, vol. 33, no. 23, pp. 6804–6839, 2008.

[74] L. Evans, “Driver Behavior Effects on Fuel Consumption in Urban Driving,” *Human Factors*, vol. 21, no. 4. pp. 389–398, 1979.

[75] T. S. Stephens, J. Gonder, Y. Chen, Z. Lin, C. Liu, and D. Gohlke, “Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles,” no. November, 2016.

[76] J. H. Gawron, G. A. Keoleian, R. D. De Kleine, T. J. Wallington, and H. C. Kim, “Life Cycle Assessment of Connected and Automated Vehicles: Sensing and Computing Subsystem and Vehicle Level Effects,” *Environ. Sci. Technol.*, vol. 52, no. 5, pp. 3249–3256, 2018.

[77] J. Lee and K. M. Kockelman, “Energy Implications of Self-Driving Vehicles.”

[78] Z. Wadud, D. MacKenzie, and P. Leiby, “Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles,” *Transp. Res. Part A Policy Pract.*, vol. 86, pp. 1–18, 2016.

[79] C. Brownell and A. Kornhauser, “Driverless Alternative: Fleet Size and Cost Requirements for a Statewide Autonomous Taxi Network in New Jersey,” *TRB Proc.*, 2014.

[80] K. E. Forrest, B. Tarroja, L. Zhang, B. Shaffer, and S. Samuelsen, “Charging a renewable future: The impact of electric vehicle charging intelligence on energy storage requirements to meet renewable portfolio standards,” *J. Power Sources*, vol. 336, pp. 63–74, 2016.

[81] B. Tarroja, B. Shaffer, and S. Samuelsen, “The importance of grid integration for achievable greenhouse gas emissions reductions from alternative vehicle technologies,” *Energy*, vol. 87, pp. 504–519, 2015.

[82] S. Wang, B. Tarroja, L. S. Schell, B. Shaffer, and S. Samuelsen, "Prioritizing among the end uses of excess renewable energy for cost-effective greenhouse gas emission reductions," *Appl. Energy*, vol. 235, pp. 284–298, Feb. 2019.

[83] T. P. Hendrickson, O. Kavvada, N. Shah, R. Sathre, and C. D Scown, "Life-cycle implications and supply chain logistics of electric vehicle battery recycling in California," *Environ. Res. Lett.*, vol. 10, no. 1, 2015.

[84] H. Huo, Y. Wu, and M. Wang, "Total versus urban: Well-to-wheels assessment of criteria pollutant emissions from various vehicle/fuel systems," *Atmos. Environ.*, vol. 43, no. 10, pp. 1796–1804, 2009.

[85] A. Lajunena and T. Lipmana, "Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses," *Energy*, vol. 106, pp. 329–342, 2016.

[86] J. A. Tunnell, Z. D. Asher, S. Pasricha, and T. H. Bradley, "Towards Improving Vehicle Fuel Economy with ADAS," *SAE Tech. Pap.*, vol. 2018-April, no. 2, pp. 1–12, 2018.

[87] M. Hyland and H. S. Mahmassani, "Dynamic autonomous vehicle fleet operations: Optimization-based strategies to assign AVs to immediate traveler demand requests," *Transp. Res. Part C Emerg. Technol.*, vol. 92, no. May, pp. 278–297, 2018.

[88] C. Yang and R. McCarthy, "Electricity Grid: Impacts of Plug-In Electric Vehicle Charging," 2009.

[89] V. Wifvat, B. Shaffer, and S. Samuelsen, "A Review of Sensor Technologies for Automotive Fuel Economy Benefits," *SAE Int. J. Connect. Autom. Veh.*, vol. 2, no. 1, pp. 5–16, 2018.

[90] L. Guvenc *et al.*, "Cooperative Adaptive Cruise Control Implementation of Team Mekar at the Grand Cooperative Driving Challenge," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 3, pp. 1062–1074, Sep. 2012.

[91] J. Ploeg, S. Shladover, H. Nijmeijer, and N. van de Wouw, "Introduction to the Special Issue on the 2011 Grand Cooperative Driving Challenge," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 3, pp. 989–993, 2012.

[92] A. Geiger, F. Moosmann, M. Lauer, and B. Ranft, "Team AnnieWAY's Entry to GCDC (2011)," *Gcdc*, pp. 1–13, 2011.

[93] C. Englund *et al.*, "The Grand Cooperative Driving Challenge 2016: Boosting the introduction of cooperative automated vehicles," *IEEE Wirel. Commun.*, vol. 23, no. 4, pp. 146–152, 2016.

[94] R. Ervin *et al.*, "Automotive Collision Avoidance System Field Operational Test Report: Methodology and Results Appendices," vol. UMTRI-2005, no. May, p. 430, 2005.

[95] S. Shogan, "Connected Vehicle Safety Pilot Overview and Infrastructure Readiness," no. August 2011, p. 37, 2013.

[96] A. Festag, R. Baldessari, W. Zhang, L. Le, A. Sarma, and M. Fukukawa, "CAR-2-X communication for safety and infotainment in Europe," *NEC Tech. J.*, vol. 3, no. 1, pp. 21–26, 2008.

[97] F. Ahmed-Zaid *et al.*, “VSC-A Final Report,” *Nhtsa*, no. September, pp. 1–102, 2011.

[98] M. Schlingelhof, D. Bétaille, and P. Bonnifait, “Advanced positioning technology approach for co-operative vehicle infrastructure systems (cvis),” *Tech. Pap. ITS …*, 2007.

[99] B. und S. (BMVBS) Bundesministerium für Verkehr, “Status und Rahmenbedingungen für Intelligente Verkehrssysteme (IVS) in Deutschland,” vol. 17, no. 1, pp. 1–165, 2010.

[100] H. Stübing, A. Jaeger, N. Bißmeyer, C. Schmidt, and S. a Huss, “Verifying Mobility Data Under Privacy Considerations in Car-To-X Communication,” pp. 1–12.

[101] S. El-Tawab and M. Abuelela, “Real-time weather notification system using intelligent vehicles and smart sensors,” in *2009 IEEE 6th International Conference on Mobile Adhoc and Sensor Systems*, 2009, pp. 627–632.

[102] H. Kurihata *et al.*, “Rainy weather recognition from in-vehicle camera images for driver assistance,” in *IEEE Proceedings. Intelligent Vehicles Symposium, 2005.*, 2005, vol. 2005, pp. 205–210.

[103] C. Dannheim, M. Mader, and J. Loewenau, “A novel approach for the enhancement of cooperative ACC by deriving real time weather information,” in *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, 2013, pp. 2207–2211.

[104] C. Harvey, R. C. McIlroy, and N. A. Stanton, “Getting drivers to do the right thing: a review of the potential for safely reducing energy consumption through design,” *IET Intell. Transp. Syst.*, vol. 8, no. 4, pp. 388–397, Jun. 2014.

[105] T. Schmits, “Cooperative Mobility Systems and Services for Energy Efficiency: High Level Architecture,” 2014.

[106] J. H. Gawron, G. A. Keoleian, R. D. De Kleine, T. J. Wallington, and H. C. Kim, “Life Cycle Assessment of Connected and Automated Vehicles: Sensing and Computing Subsystem and Vehicle Level Effects,” *Environ. Sci. Technol.*, vol. 52, no. 5, pp. 3249–3256, 2018.

[107] M. S. Temiz, S. Kulur, and S. Dogan, “Real Time Speed Estimation From Monocular Video,” *ISPRS - Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.*, vol. XXXIX-B3, no. September, pp. 427–432, 2012.

[108] M. Bibuli, M. Caccia, and L. Lapierre, “Path-following algorithms and experiments for an autonomous surface vehicle,” *IFAC Proc. Vol.*, vol. 7, no. PART 1, pp. 81–86, 2007.

[109] U.S. Energy Information Administration, “Study of the Potential Energy Consumption Impacts of Connected and Automated Vehicles,” no. March, p. 96, 2017.

[110] N. Fairfield and C. Urmson, “Traffic light mapping and detection,” *Proc. - IEEE Int. Conf. Robot. Autom.*, pp. 5421–5426, 2011.

[111] S. Hsu, S. Acharya, a. Rafii, and R. New, “Performance of a time-of-flight range camera for intelligent vehicle safety applications,” *Adv. Microsystems Automot. Appl. 2006*, pp. 205–219, 2006.

[112] J. Harding *et al.*, “Vehicle-to-Vehicle Communications : Readiness of V2V Technology for Application,” no. August, 2014.

[113] J. Gonder, M. Earleywine, and W. Sparks, “Analyzing Vehicle Fuel Saving Opportunities

through Intelligent Driver Feedback," *SAE Int. J. Passeng. Cars - Electron. Electr. Syst.*, vol. 5, no. 2, 2012.

[114] D. Lang, R. Schmied, and L. Del Re, "Prediction of Preceding Driver Behavior for Fuel Efficient Cooperative Adaptive Cruise Control," SAE International, Apr. 2014.

[115] H. Hartenstein and K. P. Laberteaux, "A tutorial survey on vehicular ad hoc networks," *IEEE Commun. Mag.*, vol. 46, no. 6, pp. 164–171, Jun. 2008.

[116] V. Milanés *et al.*, "Making Transport Safer : V2V-Based Automated Emergency Braking System Emergency Braking System," vol. 4142, no. October, 2011.

[117] M. Brackstone and M. McDonald, "Car-following: A historical review," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 2, no. 4, pp. 181–196, 1999.

[118] C. Dannheim, M. Mader, C. Icking, J. Loewenau, and K. Massow, "TEAM -- CO2 Reduction through Online Weather Assistant for Cooperative ACC Driving," in *2013 Fifth International Conference on Computational Intelligence, Communication Systems and Networks*, 2013, pp. 369–373.

[119] S. Brakatsoulas, D. Pfoser, R. Salas, and C. Wenk, "On map-matching vehicle tracking data," in *VLDB 2005 - Proceedings of 31st International Conference on Very Large Data Bases*, 2005, vol. 2, pp. 853–864.

[120] M. Kerper, C. Wewetzer, H. Trompeter, W. Kiess, and M. Mauve, "Driving More Efficiently - The Use of Inter-Vehicle Communication to Predict a Future Velocity Profile," in *2011 IEEE 73rd Vehicular Technology Conference (VTC Spring)*, 2011, pp. 1–5.

[121] J. Piao and M. McDonald, "Advanced driver assistance systems from autonomous to cooperative approach," *Transp. Rev.*, vol. 18, no. 5, pp. 659–684, 2008.

[122] B. Fleischmann, S. Gnutzmann, and E. Sandvoß, "Dynamic Vehicle Routing Based on Online Traffic Information," *Transp. Sci.*, vol. 38, no. 4, pp. 420–433, Nov. 2004.

[123] N. Rincon-Garcia, B. J. Waterson, and T. J. Cherrett, "Requirements from vehicle routing software: perspectives from literature, developers and the freight industry," *Transp. Rev.*, vol. 0, no. 0, pp. 1–22, 2017.

[124] R. Kishore Kamalanathsharma and H. A. Rakha, "Leveraging Connected Vehicle Technology and Telematics to Enhance Vehicle Fuel Efficiency in the Vicinity of Signalized Intersections," *J. Intell. Transp. Syst.*, pp. 1–12, Feb. 2014.

[125] Z. R. Li, M. V Chitturi, L. Yu, A. R. Bill, and A. David, "Sustainability Effects of Next-Generation Intersection Control For Autonomous Vehicles," vol. 4142, no. October, 2017.

[126] E. Koenders and J. Vreeswijk, "Cooperative infrastructure," in *2008 IEEE Intelligent Vehicles Symposium*, 2008, pp. 721–726.

[127] C. Raubitschek, N. Schutze, E. Kozlov, and B. Baker, "Predictive driving strategies under urban conditions for reducing fuel consumption based on vehicle environment information," in *2011 IEEE Forum on Integrated and Sustainable Transportation Systems*, 2011, pp. 13–19.

[128] T. van Keulen, G. Naus, B. de Jager, R. van de Molengraft, M. Steinbuch, and E. Aneke,

"Predictive cruise control in hybrid electric vehicles," *World Electr. Veh. J.*, vol. 3, no. 1, 2009.

[129] M. Maile *et al.*, "Cooperative intersection collision avoidance system limited to stop sign and traffic signal violations (CICAS-V)," 2008.

[130] J. Chang *et al.*, "Estimated Benefits of Connected Vehicle Applications: Dynamic Mobility Applications, AERIS, V2I Safety, and Road Weather Management Applications," no. August, p. 57p, 2015.

[131] A. J. Davison, I. D. Reid, N. D. Molton, and O. Stasse, "MonoSLAM: real-time single camera SLAM.," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 6, pp. 1052–67, Jun. 2007.

[132] E. Dagan, O. Mano, G. P. Stein, and A. Shashua, "Forward collision warning with a single camera," in *IEEE Intelligent Vehicles Symposium, Proceedings*, 2004, pp. 37–42.

[133] T. Freek Faber *et al.*, "Final results : impacts on traffic efficiency and environment," 2012.

[134] A. Gern, U. Franke, and P. Levi, "Robust vehicle tracking fusing radar and vision," in *IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 2001, pp. 323–328.

[135] A. Gern, U. Franke, and P. Levi, "Advanced lane recognition - fusing vision and radar," in *IEEE Intelligent Vehicles Symposium, Proceedings*, 2000, pp. 45–51.

[136] A. Barth and U. Franke, "Estimating the Driving State of Oncoming Vehicles From a Moving Platform Using Stereo Vision," *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 4, pp. 560–571, Dec. 2009.

[137] Z. Ji, M. Luciw, J. Weng, and S. Zeng, "Incremental Online Object Learning in a Vehicular Radar-Vision Fusion Framework," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 402–411, Jun. 2011.

[138] US NREL, "FASTSim Publications," 2019. [Online]. Available: https://www.nrel.gov/transportation/fastsim-publications.html.

[139] A. Rousseau *et al.*, *Electric drive vehicle development and evaluation using system simulation*, vol. 19, no. 3. IFAC, 2014.

[140] US DOE, "Vehicle Technologies Office: Modeling and Simulation," 2019. [Online]. Available: https://www.energy.gov/eere/vehicles/modeling-and-simulation.

[141] K. R. Den Braven, A. Abdel-rahim, and A. Battles, "Modeling Vehicle Fuel Consumption and Emissions at Signalized Intersection Approaches: Integrating Field-Collected Data," no. July, 2012.

[142] W. F. Faris, H. A. Rakha, R. I. Kafafy, M. Idres, and S. Elmoselhy, "Vehicle fuel consumption and emission modelling: an in-depth literature review," *Int. J. Veh. Syst. Model. Test.*, vol. 6, no. 3/4, p. 318, 2011.

[143] E. Grumert, *Cooperative Variable Speed Limit Systems Modeling and Evaluation using Microscopic Traffic Simulation*, no. 1670. 2014.

[144] J. C. Dias, P. H. Abreu, D. C. Silva, G. Fernades, P. Machado, and A. Leitão, "2 Preparing Data for Urban Traffic Simulation using SUMO," *1st SUMO User Conf. 2013*, pp. 25–34,

2013.

[145] W. Niebel, “Cost-Benefit-Based Implementation Strategy for Green Light Optimised Speed Advisory (GLOSA),” *Commun. Comput. Inf. Sci.*, vol. 395 CCIS, no. C, pp. 313–320, 2013.

[146] H. Noori, “Modeling and Simulation of Vehicle to Vehicle and Infrastructure Communication in Realistic Large Scale Urban Area,” no. June, 2013.

[147] P. M. D’Orey, “Vehicular Communications for Efficient and Sustainable Mobility,” 2014.

[148] B. Van Arem and M. M. Mahmod, “A simulation framework for modelling the impacts of an integrated road-vehicle system on local air quality,” no. October, pp. 1–15, 2008.

[149] F. Hagenauer, F. Dressler, and C. Sommer, “A simulator for heterogeneous vehicular networks,” *IEEE Veh. Netw. Conf. VNC*, vol. 2015-Janua, no. January, pp. 185–186, 2015.

[150] B. Schünemann, “V2X simulation runtime infrastructure VSimRTI: An assessment tool to design smart traffic management systems,” *Comput. Networks*, vol. 55, no. 14, pp. 3189–3198, Oct. 2011.

[151] I. Telsa, “Tesla First Quarter 2019 Update, Started production of Full Self Driving computer,” 2019.

[152] M. Olsson, “Designing and Optimizing Side-View Mirrors,” 2011.

[153] Elio Motors, “Elio Motors: The Ultimate Commuter Vehicle,” 2019. [Online]. Available: https://www.eliomotors.com/.

[154] I. Tesla, “Model 3,” 2019. [Online]. Available: https://www.tesla.com/model3.

[155] US DOE, “New All-Electric Vehicles, Sorting based on EPA Combined City/Hwy MPG,” 2019. [Online]. Available: https://www.fueleconomy.gov/feg/PowerSearch.do?action=alts&path=3&year1=2019&year2=2020&vtype=Electric&srchtyp=newAfv.

[156] US DOE, “Compare Fuel Cell Vehicles,” 2019. [Online]. Available: https://www.fueleconomy.gov/feg/fcv_sbs.shtml.

[157] US EPA, “Dynamometer Drive Schedules: Quick Graphic Review of Driving Schedules EPA Vehicle Chassis Dynamometer Driving Schedules (DDS),” 2018. [Online]. Available: https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules.

[158] Z. Xu, X. Li, X. Zhao, M. H. Zhang, and Z. Wang, “DSRC versus 4G-LTE for connected vehicle applications: A study on field experiments of vehicular communication performance,” *J. Adv. Transp.*, vol. 2017, 2017.

[159] ROMBERG GF, F. CHIANESE, and LAJOIE RG, “Aerodynamics of Race Cars in Drafting and Passing Situations,” *SAE Pap 710213*, 1971.

[160] M. Zabat, S. Frascaroli, and F. K. Browand, “Drag measurements on 2, 3 and 4 car platoons,” *SAE Tech. Pap.*, no. 41 2, 1994.

[161] M. Zabat, N. Stabile, S. Frascaroli, and F. Browand, “Drag forces experienced by 2, 3 and 4-vehicle platoons at close spacings,” *SAE Tech. Pap.*, no. 41 2, 1995.

[162] P. Schito and F. braghin, “Numerical and Experimental Investigation on Vehicles in Platoon,” *SAE Int. J. Commer. Veh.*, vol. 5, no. 1, pp. 63–71, 2012.

[163] G. Le Good, M. Resnick, P. Boardman, and B. Clough, “Effects on the Aerodynamic Characteristics of Vehicles in Longitudinal Proximity Due to Changes in Style,” *SAE Tech. Pap.*, vol. 2018-May, no. May, 2018.

[164] S. Pagerit, P. Sharer, and A. Rousseau, “Fuel Economy Sensitivity to Vehicle Mass for Advanced Vehicle Powertrains,” *SAE Tech. Pap.*, 2006.

[165] California Department of Transportation (CALTRANS), “Park and Ride Program Resources Guide 2010,” 2010.

[166] G. Circella, A. McFadden, and A. Farzad, “California Beyond SB 375: Evaluating the Impact of Proposed Land Use and Transportation Plans on Future Travel Patterns and Interregional Travel Behavior,” 2014.

[167] D. S. Bunch and D. Brownstone, “Energy Commission Models for Analyzing and Projecting Household Transportation Energy Demand: Evaluation, Model Improvement Options, and Recommendations,” 2016.

[168] N. McGuckin and A. Fucci, “Summary of Travel Trends 2017 National Household Travel Survey,” 2018.

[169] L. R. Chinkin *et al.*, “Weekday versus weekend activity patterns for ozone precursor emissions in california’s south coast air basin,” *J. Air Waste Manag. Assoc.*, vol. 53, no. 7, pp. 829–843, 2003.

[170] California Air Resources Board, “EMFAC2017 Volume III - Technical Documentation (V1.0.2),” 2018.

[171] D. J. Fagnant and K. M. Kockelman, “The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios,” *Transp. Res. Part C Emerg. Technol.*, vol. 40, pp. 1–13, 2014.

[172] J. Cramer and A. B. Krueger, “Disruptive change in the taxi business: The case of uber,” *Am. Econ. Rev.*, vol. 106, no. 5, pp. 177–182, 2016.

[173] A. Henao and W. E. Marshall, “The impact of ride-hailing on vehicle miles traveled,” *Transportation (Amst).*, no. 0123456789, 2018.

[174] N. Agatz, A. Erera, M. Savelsbergh, and X. Wang, “Optimization for dynamic ride-sharing: A review,” *Eur. J. Oper. Res.*, vol. 223, no. 2, pp. 295–303, 2012.

[175] C. Rodier, F. Alemi, and D. Smith, “Dynamic ridesharing: Exploration of potential for reduction in vehicle miles traveled,” *Transp. Res. Rec.*, vol. 2542, pp. 120–126, 2016.

[176] P. Santi, G. Resta, M. Szell, S. Sobolevsky, S. H. Strogatz, and C. Ratti, “Quantifying the benefits of vehicle pooling with shareability networks,” *Proc. Natl. Acad. Sci. U. S. A.*, vol. 111, no. 37, pp. 13290–13294, 2014.

[177] J. Viegas, L. Martinez, P. Crist, and S. Masterson, “Shared Mobility. Inovation for Liveable Cities,” *Int. Transp. Forum’s Corp. Partnersh. Board*, pp. 1–56, 2016.

[178] A. Amey, “A Proposed Methodology for Estimating Rideshare Viability within an Organization , applied to the MIT Community,” *Transp. Res. Board 90th Annu. Meet. No.*

11-2585. 2011, no. April 2010, pp. 1–16, 2011.

[179] San Francisco County Transportation Authority and Cambridge Systematics Inc., "San Francisco Travel Demand Forecasting Model Development: Executive Summary," 2002.

[180] W. Burghout, P.-J. Rigole, and I. Andreasson, "Impacts of shared autonomous taxis in a metropolitan area," *Proc. 94th Annu. Meet. Transp. Res. Board*, no. March 2016, 2015.

[181] M. Heilig, T. Hilgert, N. Mallig, M. Kagerbauer, and P. Vortisch, "Potentials of Autonomous Vehicles in a Changing Private Transportation System - A Case Study in the Stuttgart Region," *Transp. Res. Procedia*, vol. 26, no. 2016, pp. 13–21, 2017.

[182] ITF, "Urban Mobility System Upgrade: How shared self-driving cars could change city traffic," *Corp. Partnersh. Board Rep.*, pp. 1–36, 2015.

[183] K. Winter, O. Cats, G. Correia, and B. van Arem, "Performance analysis and fleet requirements of automated demand-responsive transport systems as an urban public transport service," *Int. J. Transp. Sci. Technol.*, vol. 7, no. 2, pp. 151–167, 2018.

[184] B. Tarroja, "Advising and Optimizing the Deployment of Sustainability-Oriented Technologies in the Integrated Electricity, Light-Duty Transportation, and Water Supply System," 2014.

[185] B. Tarroja, J. D. Eichman, L. Zhang, T. M. Brown, and S. Samuelsen, "The effectiveness of plug-in hybrid electric vehicles and renewable power in support of holistic environmental goals: Part 1 Evaluation of aggregate energy and greenhouse gas performance," *J. Power Sources*, vol. 257, no. 2014, pp. 461–470, 2013.

[186] Energy and Environmental Economics Inc., "Deep Decarbonization in a High Renewables Future Updated Results from the California PATHWAYS Model," 2018.

[187] M. Berglund *et al.*, "Health risk evaluation of nitrogen oxides," *Scand. J. Work. Environ. Health*, pp. 1–72, 1993.

[188] J. M. Samet, F. Dominici, S. L. Zeger, J. Schwartz, and D. W. Dockery, "The National Morbidity, Mortality, and Air Pollution Study. Part I: Methods and methodologic issues," *Res. Rep. Health. Eff. Inst.*, no. 94 Pt 1, p. 5, 2000.

[189] T.-M. Chen, W. G. Kuschner, J. Gokhale, and S. Shofer, "Outdoor air pollution: nitrogen dioxide, sulfur dioxide, and carbon monoxide health effects," *Am. J. Med. Sci.*, vol. 333, no. 4, pp. 249–256, 2007.

[190] M. Q. Wang, "GREET 1.5-Transportation Fuel-Cycle Model: Volume 1: Methodology, Development, Use, and Results," 1999.

[191] US EPA, "Emission Facts: Average Annual Emissions and Fuel Consumption for Passenger Cars and Light Trucks," *Environ. Prot.*, no. EPA420-F-00–013, pp. 2–4, 2000.

[192] U.S. Department of Transportation Federal Highway Administration, "Transporation Air Quality Selected Facts and Figures," no. February, 2016.