U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

SMART Mobility

Connected and Automated Vehicles Capstone Report

July 2020

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Foreword

The U.S. Department of Energy's Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium is a multiyear, multi-laboratory collaborative, managed by the Energy Efficient Mobility Systems Program of the Office of Energy Efficiency and Renewable Energy, Vehicle Technologies Office, dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The first three-year research phase of SMART Mobility occurred from 2017 through 2019 and included five research pillars: Connected and Automated Vehicles, Mobility Decision Science, Multi-Modal Freight, Urban Science, and Advanced Fueling Infrastructure. A sixth research thrust integrated aspects of all five pillars to develop a SMART Mobility Modeling Workflow to evaluate new transportation technologies and services at scale.

This report summarizes the work of the Connected and Automated Vehicles (CAVs) Pillar. This Pillar investigated the energy, technology, and usage implications of vehicle connectivity and automation and identified efficient CAV solutions. For information about the other Pillars and about the SMART Mobility Modeling Workflow, please refer to the relevant Pillar's Capstone Report.

Acknowledgments

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Abbreviations

AADT	average annual daily traffic
ABM	agent-based -models
ACC	adaptive cruise control
ADAS	advanced driver-assistance system
ADS	automated driving system
ADT	average daily traffic
AEO	Annual Energy Outlook
AES	automated electric shuttle
AEV	automated electric vehicle
AFDC	Alternative Fuels Data Center
AFI	Advanced Fueling Infrastructure
API	application programming interface
ASCM	active safety control module
ATM	active traffic management
AV	automated vehicle
BAU	business-as-usual
BEV	battery electric vehicle
CACC	cooperative adaptive cruise control
CAN	control area network
CAV	connected and automated vehicle
CC	cruise control
CGM	central gateway module
CMIP	charging management and infrastructure planning
C-rate	charging rate
CRM	coordinated ramp metering
DOE	U.S. Department of Energy
DSRC	dedicated short range communication
EAD	eco-approach and departure
E-CAV	electrified connected and automated vehicles
ECU	engine control unit
EIA	Energy Information Administration
EPA	U.S. Environmental Protection Agency
EV	electric vehicle
FHWA	Federal Highway Administration
FMVSS	Federal Motor Vehicle Safety Standards
GHG	greenhouse gas
GNSS	Global Navigation Satellite System
GPS	Global Position System

HD	heavy-duty
HDCAV	connected and automated heavy-duty vehicle
HDV	heavy-duty vehicle
HEV	hybrid electric vehicle
HPMS	Highway Performance Monitoring System
HWFET	Highway Fuel Economy Test
I2V	infrastructure-to-vehicle
ICE	internal combustion engine
ICEV	internal-combustion-engine vehicle
KNN	K-nearest neighbors
LCV	long combination vehicle
LD	light-duty
LDCAV	connected and automated light-duty vehicle
LDV	light-duty vehicle
LRRM	local responsive ramp metering
MEP	mobility energy productivity
MiM	man-in-the-middle
MOE	measure of effectiveness
MPO	Metropolitan Planning Organization
MV	manually driven vehicle
MY	model year
NGSIM	Next Generation Simulation
NHTS	national household travel survey
NREL	National Renewable Energy Laboratory
ODD	operational design domain
PCM	powertrain control module
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
PID	proportional-integral-derivative controller
PMT	passenger-miles traveled
RF	random forest
SAES	shared automated electric shuttle
SAEV	shared automated electric vehicles
SAVs	shared automated vehicles
SMART	Systems and Modeling for Accelerated Research in Transportation
SPaT	signal phase and timing

TCO	total cost of ownership
TMC	traffic management center
TNC	transportation network company
TRR	Transportation Research Record
TSDC	Transportation Secure Data Center
TTD	total travel distance
TTT	total travel time
UDDS	Urban Dynamometer Driving Schedule
UMR	Urban Mobility Report
UMS	Urban Mobility Scorecard
U.S.	United States
V2I	vehicle-to-infrastructure
V2V	vehicle-to-vehicle
V2X	vehicle-to-anything
VMT	vehicle miles traveled
VOTT	value of travel time
VSL	variable speed limit
VSL/VSA	variable speed limits/variable speed advisories
ZOV	zero occupancy vehicles

Executive Summary

Connectivity and Automation Can Lead to Significant Changes to Both Overall Efficiency and Usage

The continued growth of connected and automated vehicle (CAV) technologies is anticipated to significantly change the way vehicles move and the way travelers achieve mobility. This will have a significant impact on energy consumption, as well as many other facets of transportation, at scales ranging from the individual vehicle level to the transportation system level. CAV technologies are unique in that they can positively *and* negatively impact efficiency (both energy efficiency and passenger/freight efficiency) as well as vehicle miles traveled (VMT) and related metrics. In addition, the interactions between connectivity and automation-enabled technologies and the powertrain technologies to which they are applied will determine whether the impact of a particular technology solution (CAV or powertrain) will be positive or negative, based on the synergies between the new operating profile afforded by the connectivity and automation and the specific powertrain under analysis. For example, the energy benefits of regenerative braking in electrified powertrains are decreased in an environment where most vehicle transients are removed through improved vehicle cooperation and profile smoothing.

Before the initiation of the DOE SMART Mobility Laboratory Consortium, the Department of Energy conducted a study to address the ranges (bounds) of potential effects of CAV technologies on VMT and vehicle fuel efficiency.[1] That report laid the foundation for the subsequent SMART Consortium efforts discussed in this report and identified research gaps to be assessed in greater detail by the consortium's efforts. Based on a review and synthesis of existing CAV literature, the bounding study concluded that there is enormous uncertainty about potential impacts on long-term VMT and efficiency if fully automated and highly connected vehicles replace nearly all light-duty passenger vehicles in the United States. (The bounding study used 100% penetration of new technologies for each assessment case.) Scenarios representing the lower and upper bounds of changes in fuel use for a national fleet of conventional powertrain vehicles were assessed, with projected energy consumption decreasing by as much as 60% of current U.S. light-duty vehicle (LDV) fuel consumption or increasing as much as two times (200%). The wide range between the lower and upper bounds of future vehicle energy use reflects the large uncertainties regarding ways that CAVs can potentially influence vehicle efficiency and use through changes in vehicle design, purpose of use, driving, travel behavior, management, and policies. The report grouped the factors impacting national-level fuel consumption into three primary categories: vehicle fuel consumption per mile, travel demand or VMT, and CAV adoption. Within these primary categories, the report also highlighted the most important data and knowledge gaps identified by the literature synthesis and impact analysis: 1) travel demand impacts due to automation and connectivity, 2) CAV adoption and market dynamics, 3) fuel (and energy) efficiency impacts due to connectivity and automation, and 4) connectivity and automation insights for heavy-duty vehicles. Aided by this foundational research work, the CAVs Pillar within DOE's SMART Mobility Consortium investigated the above key research priorities while also understanding synergies with connectivity and automation for both conventional and electrified vehicles.

U.S. Department of Energy's Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Connected and Automated Vehicle Pillar

CAV technologies offer the potential for improving vehicle efficiency and possibly reducing overall transportation energy use through improved control and optimization, from the vehicle level to the corridor level and up to the city/regional scale. Connectivity and automation may also stimulate further vehicle electrification due to more convenient, transparent, and informed BEV charging and usage. However, the various levers for increased vehicle and transportation efficiency are at risk of being negated by an increase in VMT, due to possible rebound effects (driving more because connectivity and/or automation makes it easier and/or cheaper) as well as new use cases. Therefore, a systems-centric research effort is necessary to more comprehensively identify energy saving opportunities while developing strategies to mitigate operational inefficiencies to the largest degree possible.

This work studies CAV technologies using reliable models, analytical methods, and experimentation to predict the energy and mobility implications of CAVs and their associated infrastructure components across a range of technology development, market penetration, and traveler behavior scenarios. More specifically, this work seeks to address three primary research questions:

- How will connected and automated vehicles and systems behave in the real world?
- What are the GHG, energy, technology and usage implications of connectivity, automation, and the combination of both technologies?
- What is the best way to harness CAVs for reduced energy use and improved mobility in transportation?

Key Findings

CAV-Focused Experimental Research and Analysis

Addressing the first research question regarding how CAV systems behave in the real world, the experimental focus of these efforts sought to create experimentally driven insights and validation data to act as a foundation and point-of-reference for subsequent simulation focused efforts. Specifically, the modeling and analytical techniques used to predict the vehicle-level, local, regional and national impacts of CAV systems depend heavily on real-world experimental data for validation. Fortunately, by leveraging available prototype and commercially available systems, effective CAV platforms for implementation of energy-saving control system designs were created and tested under a range of realistic conditions. The resulting behaviors and performance of these platforms were then used for updating simulation models and validating analytical assumptions, overcoming one of the most significant limitations to previous efforts to model the impacts of CAV systems.

Heavy-Duty Truck Cooperative Adaptive Cruise Control (CACC) and Platooning Field Research

- Combining the fuel savings potential demonstrated for truck platoons via comprehensive track-testing executed with a data-driven analysis of opportunities for Class 8 truck platooning, analysis done by the CAVs Pillar suggests that truck platooning could be an effective fuel saving strategy nationally. If the nation's truck fleet were to save the demonstrated 6.4% of its fuel with conservatively spaced two-truck platoon teams on 56% of its miles traveled (as estimated by the platoon opportunities study), the overall reduction in fuel consumption would be approximately 1.1 billion gallons of fuel per year (roughly 0.5% of U.S. transportation energy use in 2016), resulting in a 10.7 million metric tons reduction in CO_2 emissions. Platoons of three close-following trucks achieving a combined 13% reduction in fuel consumption would save close to 2.1 billion gallons of fuel per year.

While vehicle-to-vehicle (V2V)-based cooperative heavy-duty vehicle systems are nearing commercialization, there is a knowledge gap in terms of the performance, reliability, and resiliency of these systems. The CAVs Pillar studied the potential energy savings of such systems. This test track-based effort produced the most comprehensive set of platooning energy consumption test results to date. The findings confirmed some phenomena observed in previous tests and also produced new findings. The primary trends in energy consumption as a function of the gap size between the trucks are illustrated below, for each individual truck and for the two-truck and three-truck platoons as a whole.

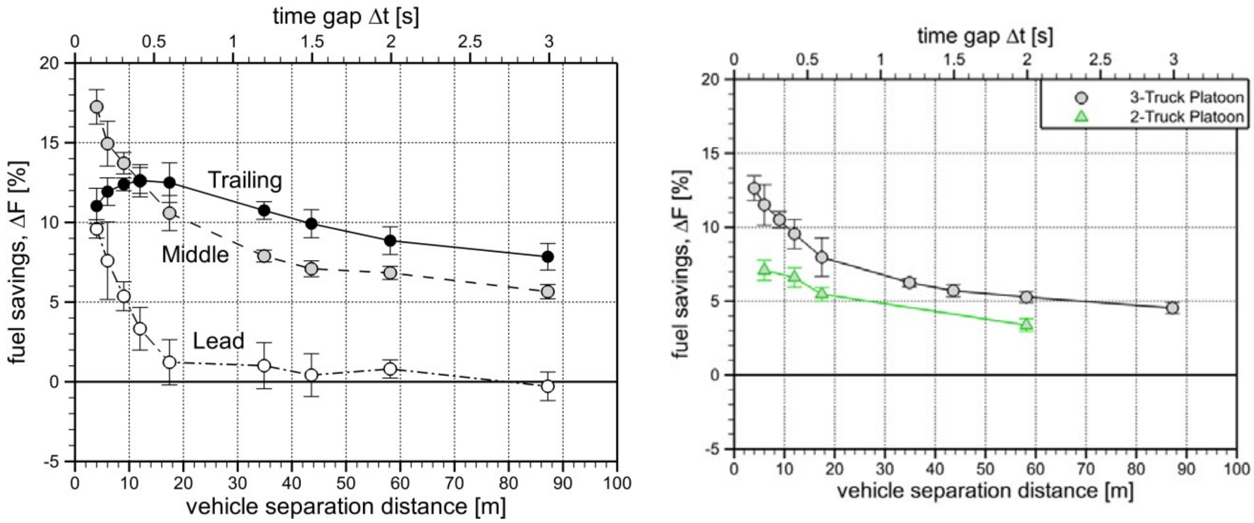

Figure 1. Fuel Savings for Individual Trucks as a Function of Separation Distance (left) and Average Fuel Savings for Two- and Three-Truck Platoons (right).

Figure 1 (left) above shows the fuel savings for each of the three trucks in a cooperative adaptive cruise control (CACC) platoon as a function of the separation distance (bottom scale) or time gap (top scale) at a speed of 105 km/h. Note that the lead truck only saves significant energy at gaps of 18 m or less, but the middle and trailing trucks save 6% and 8% respectively even as far apart as 87 m. At gaps below 18 m, the relationships become more complicated, with the lead truck's savings rising rapidly toward 10% as the gap decreases to 4 m, and the middle truck's savings rising rapidly toward 17% at the 4 m gap. In contrast, the trailing truck's energy savings peak at about 13% in the 15 m range and then decline to 11% as the gap reduces to 4 m. These trends are the consequence of different aerodynamic phenomena at the front and rear of each truck. Figure 1 (right) illustrates the average savings across the entire three-truck platoon, trending from about 5% at the 87 m gap up to 13% at the 4 m gap. It also shows a similar trend for a two-truck platoon, but with noticeably lower savings, ranging from about 2% less than the three-truck platoon at a 58 m gap to 5% less at a 6 m gap.

While the fuel savings opportunities related to Class-8 truck platooning discussed above are promising for CACC-enabled close following/platooning vehicles operating in highway environments, many unknowns can influence the actual savings during real-world operation. Specific to this investigation were 1) time spent at speeds appropriate for observable aerodynamic benefits, and 2) the availability of a partner vehicle with which to platoon.

A study in collaboration with Volvo Trucks North America analyzed a two-week period of Volvo Trucks' telematics data from over 57,000 unique vehicles traveling more than 210 million miles, which included 11 million GPS waypoints, during the summer of 2016. Telematics data from this study were used to identify opportunities in which both a partner vehicle and acceptable operating conditions were observed. The data also indicated that the East Coast, West Coast, and urban areas of the United States have higher temporal variability than the central part of the country. Analysis using a highway-speed-based cut-off to define platoonable miles (i.e., speeds at which platooning would be aerodynamically beneficial) suggested that 63% of total miles driven at known hourly average speeds may have potential for platooning.

When the availability of nearby Volvo-only partner vehicles was considered, results indicate that 56% of all classifiable miles driven were platoonable, but the platooning opportunity potential could possibly be greater with inter-manufacturer platooning. Figure 2 highlights the spatial distribution of these partner-availability-based platoonable observations for a single day snapshot. The highest regions of platoonability occur across major shipping corridors and interstate highways. Urban areas, particularly those in dense regions on the East

Coast, West Coast, and Great Lakes, appear to have fewer opportunities than West and Midwest regions though lower speed limits in west coast states were not taken into consideration.

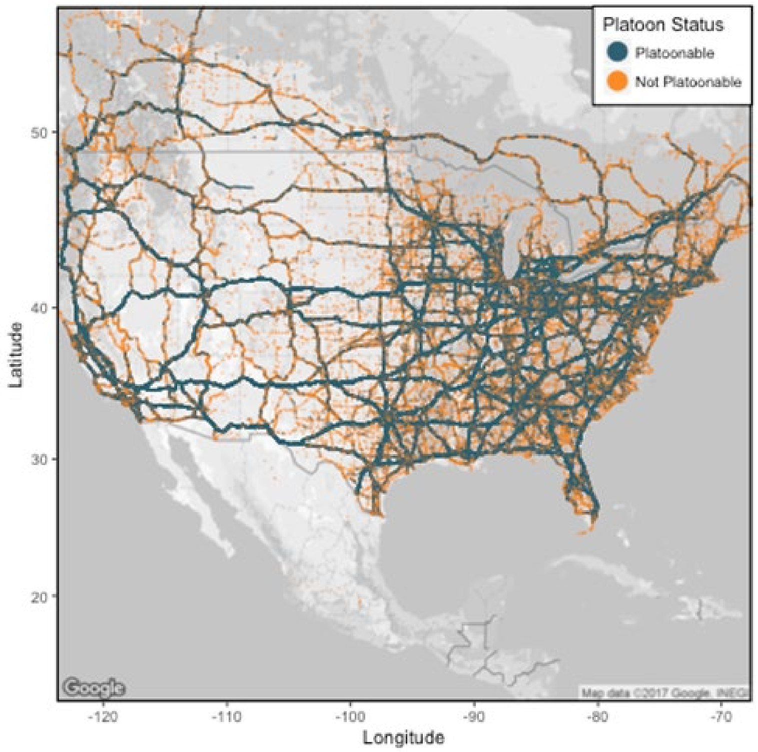

Figure 2. Snapshot of US platoonability based on partner analysis for a single day. Observations with speeds less than 30 mph are omitted for clarity.

Analysis of Class-8 Truck Platooning Dynamic Air Flow

The heavy-duty CACC work described above has shown the promise of significant fuel-savings for a range of truck platooning configurations, but also raised questions about the air-flow effects of these strategies on aerodynamic drag and engine temperatures. To support research into these questions, additional onboard instrumentation was installed on the experimental vehicles to gain a deeper understanding of the air-flow dynamics and interactions between multiple vehicles. Using this supplemental instrumentation, with a goal of explaining the reduced savings at close following distances for the last vehicle in a platoon, detailed data analysis was performed for specific cases, including the air flow experienced by the trailing truck, along with turbulence changes at the close following distances where reduced trailing vehicle fuel savings were observed, and the impacts of platooning position on engine-cooling in different formations due to reduced airflow.

Data analysis indicates non-linear patterns in the data trends for wind angle, wind speed, turbulence and temperatures for the closer following distances where a fuel savings decrease for the trailing vehicle was documented. Figure 3 illustrates the magnitude and angle of wind experienced by each truck in a three-truck platoon over a range of distances. Note that while the lead vehicle always has a mean wind speed of 29 m/s (65 mph) the following trucks start to see significantly slower speeds and higher angles of wind when closer than 35 m. At distances of 12 m and less the radar plots take on an arrowhead shape—indicating turbulence by high variability in both angle and speed—and this turbulence correlates with the distances at which following trucks exhibit a drop in fuel savings.

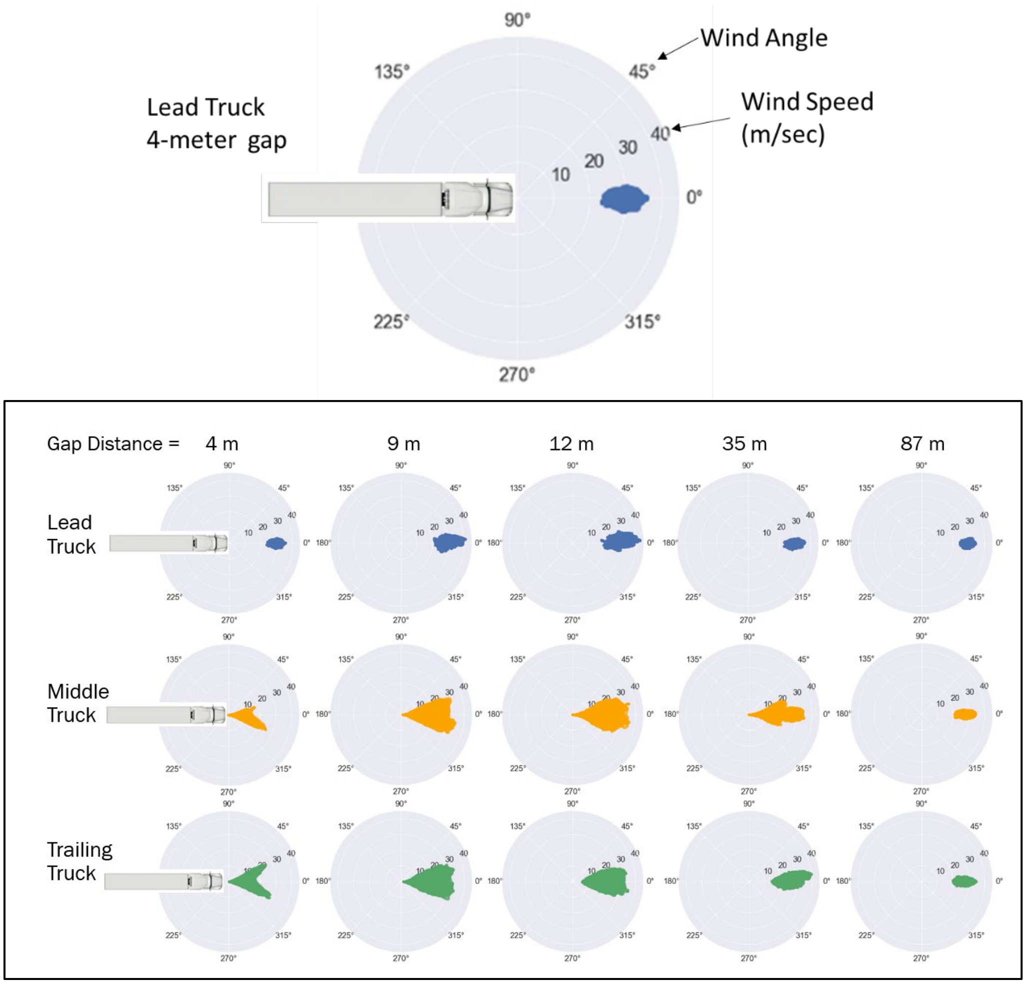

Figure 3. Magnitude and angle of wind radar plots.

In-field Assessment of Large-Scale, Light-Duty Adaptive Cruise Control (ACC) Fleet Pilot Data — Methods to Quantify On-Road Efficiency Benefits

- Analysis done by the CAVs Pillar using 18,590 trips from the Volvo Drive Me pilot study, operated in Gothenburg Sweden, showed that Adaptive Cruise Control has the potential to lower fuel consumption by 5%–7% at the individual vehicle level, compared to manually driven vehicles operating within the same study environment.

Overall on-road fuel efficiency of CAV technologies can be difficult to quantify, as the fuel efficiency of a given CAV technology compared to a fully human-controlled vehicle can vary in different driving contexts. The CAVs Pillar developed a methodology that considers the difference in fuel efficiency between a CAV and manually driven vehicle in a wide array of driving conditions or contexts and quantifies the overall impact by weighting the specific driving-context fuel efficiency differences by the amount of driving that occurs in each context. In collaboration with Volvo Cars, this methodology was demonstrated in a partial automation technology context over a large on-road dataset of vehicles operating with and without adaptive cruise control (ACC). While many studies have identified fuel saving potential from ACC strategies, the literature remains limited in terms of real-world vehicle-level operational and energy consumption differences between this type of automated driving behavior and comparable manually driven vehicles under various driving conditions. The Volvo Cars collaboration helped to fill this information gap and explored the proposed methodology's potential to quantify overall CAV technology on-road fuel efficiency— an objective of interest not only for ACC but also for higher-level CAV technologies. For this research, Volvo diesel automatic models (V70, XC70, V60) were driven by Volvo Cars employees and family members on more than 18,590 trips over the "Drive Me" route in Gothenburg, Sweden, between 2010 and 2011. Vehicles were equipped with ACC, which used a radar sensor to detect the distance to the vehicle ahead and adjust the ACC-equipped vehicle's speed to maintain a preferred gap between the vehicles. Fuel consumption data were collected from the vehicles' data bus at a 10-Hz sampling rate.

The figure below illustrates the estimated annual distribution of all vehicle travel that occurred on the designated driving network in each combination of traffic speed and road grade condition. The vehicle travel distance weighting and sensitivity scenario evaluation process revealed that, on an individual vehicle level, these ACC-operating vehicles consumed 5%–7% less fuel than the fully manually driven vehicles over the designated driving network. Other considerations for automated vehicle fuel use include their types/specific implementations and penetration levels into traffic. For instance, while the ACC vehicles in this Volvo Cars study operated mostly around other vehicles with the driver in complete control, other studies have shown that a large number of ACC vehicles operating together can make traffic worse, due to the lag for each vehicle to detect speed changes and other factors leading to amplification of disturbances. As will be discussed later in this report, it is possible for high automation penetration to improve rather than impair overall traffic flow if it includes vehicle-to-vehicle communication, enabling cooperative ACC (CACC).

		% Grade Bins									
	VKT (unit: million)	(-5, -4]	(-4, -3]	(-3, -2]	(-2, -1]	(-1, 0]	(0, 1]	(1, 2]	(2, 3]	(3, 4]	(4, 5]
Speed Bins (kmph)	(0, 10]	0.03	0.12	0.15	0.13	1.73	1.31	0.42	0.19	0.04	0.02
	(10, 20]	0.22	0.19	0.50	0.82	4.86	5.59	1.16	0.64	0.10	0.09
	(20, 30]	0.48	0.70	1.38	1.57	9.03	9.44	1.90	1.22	0.17	0.15
	(30, 40]	0.78	0.88	1.98	2.05	13.19	12.13	2.95	2.14	0.35	0.44
	(40, 50]	1.21	1.49	3.38	3.23	23.32	19.45	3.63	3.64	1.09	0.94
	(50, 60]	3.67	4.69	8.54	8.19	51.73	34.90	8.74	9.70	4.60	2.24
	(60, 70]	9.90	13.73	19.48	32.11	130.93	89.55	33.02	28.82	17.10	6.74
	(70, 80]	9.04	14.16	28.23	50.57	214.64	164.88	62.58	27.19	15.78	7.89
	(80, 90]	4.05	5.25	15.02	23.26	229.98	152.27	30.53	7.76	4.71	1.58
	(90, 100]	0.62	0.64	5.49	6.18	161.99	87.78	11.52	1.35	0.59	0.21
	(100, 110]	0.07	0.09	0.49	0.61	28.44	18.98	1.55	0.32	0.08	0.03

Figure 4. Variation in estimated overall annual vehicle travel on the designated driving network in Gothenburg (in millions of vehicle kilometers travelled) organized by speed and grade bins (high values in red/orange, moderate in yellow and low in green).

The fuel economy calculation approach featured in this work can be applied to simulations of hypothetical future technology penetration scenarios as well as to data from the latest vehicle technologies operating in current traffic conditions. With automated vehicles possessing enhanced data collection and connectivity capabilities, the proposed approach could provide increased visibility into how on-road fuel economy evolves with changes in vehicle automation technology, penetration rates, and traffic impacts. Such transparency is important for stakeholders and policymakers who wish to measure technology impacts on transportation energy use and for automakers who wish to get credit for potential fuel-saving features of automated vehicle technologies.

Real-World Driving Data and Strategies for Green Routing Applications

- Leveraging data on 45,000 actual trips, a large-scale green routing opportunity evaluation done by the CAVs Pillar found that a less energy-consuming route alternative existed for about one-third of the total trips. For routes where a lower energy alternative was identified, the average energy reduction benefit of following the “greenest” route was estimated to be 12%. Interestingly, roughly half of the “greenest” route alternatives in the study also had lower travel times, suggesting a “double win” of both faster and more efficient travel.

Green-routing tools enable the selection of travel routes that minimize energy consumption and present an important fuel savings opportunity for CAV technologies. The CAVs Pillar developed, validated, and applied a methodology, called RouteE, that considers the relationship between driving conditions (road type, grade, traffic, etc.) and energy consumption for a given vehicle. The focused validation activity included collecting on-road fuel consumption data from identical pairs of conventional, hybrid, and plug-in hybrid electric vehicles driven along different routes between the same origins and destinations as well as analyzing the developed tool’s performance on a much larger scale real-world dataset. The validation effort successfully demonstrated the methodology’s ability to accurately predict which route alternative would be the “greenest” (i.e., consume the least amount of fuel), with actual energy consumption differences between the measured route pairs varying from roughly no difference to over 20% difference.

A broader green routing opportunity analysis used a larger database of real-world routes provided by NREL’s Transportation Secure Data Center (TSDC) and compared the time and energy for alternative routes to the actual route chosen by drivers. Specifically, matched origin/destination pairs from 45,000 trips in the TSDC were fed into a routing application programming interface (API) from Google Maps, along with the day of week and time of day that the actual route was driven. Based on this information, the API returned the most viable route options between each origin/destination pair (along with their estimated travel times), and RouteE was used to estimate the energy consumption for each of the route options. The analysis found that for conventional vehicles a potentially less energy-consuming route alternative existed for 31% of these actual routes. Among this subset of trips with a fuel saving route alternative, the aggregate fuel consumption of the “greenest” routes was estimated to be 12% lower than that of the originally selected routes. When considering the travel time impacts of these alternative energy saving routes, it was found that about half of them resulted in shorter travel times as well as fuel savings, with the other half incurring a travel time penalty. The figure below shows the estimated energy savings and travel time impacts for the subset of real-world trips with energy savings potential. A promising finding in this combined assessment of fuel savings and travel time impacts is that “double win” routes (where both fuel and time savings occur) account for two-thirds of the overall energy savings—underscoring the substantive and potentially easy-to-achieve opportunity that green routing could provide for connectivity-enabled vehicle fuel savings.

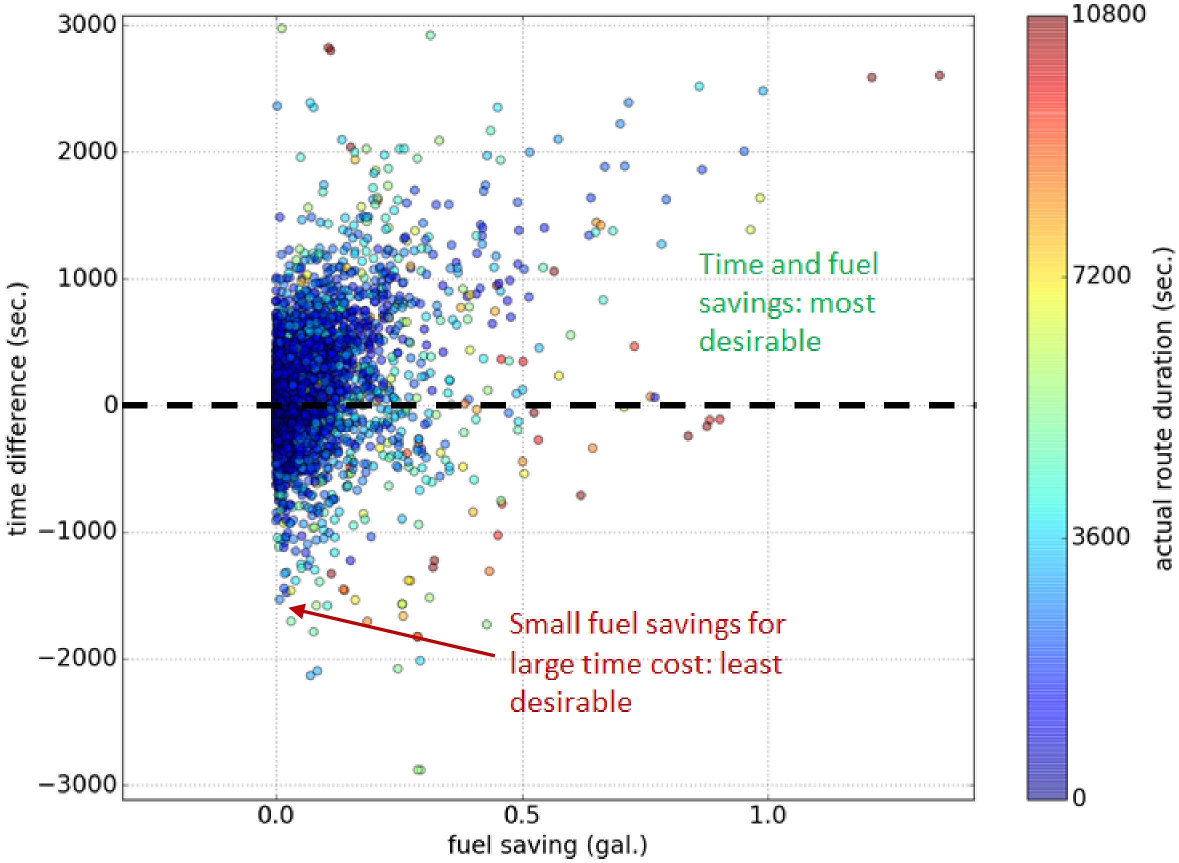

Figure 5. Energy savings vs. time savings for alternative routes compared to actual routes.

Accessory Loads and Sensitivities for Automated Vehicles

- While the computational loads for fully automated vehicles are still highly uncertain, testing and analysis done within the CAVs Pillar has shown that certain automated eco-driving capabilities can be enabled at electrical loads much lower than the 2-4kW observed from recent fully-automated vehicle fleets. Field-testing of an automated vehicle prototype, provided by an industrial project partner, found automation loads ranging between 300W and 400W for functionalities including hands-free highway operation (L3) and fully self-driving operation and navigation at lower speeds (L4). Field-testing of a Cadillac CT6 with Super Cruise, a L2+ automation system, revealed automation-related loads of approximately 100 W. Furthermore, the Super Cruise's automation loads changed minimally when the system was deactivated, suggesting that the true accessory load penalty for some lower-level automation capabilities may be minimal as these systems are already in-use for driver assistance and collision avoidance features.

Vehicle automation, especially higher-level capabilities that require minimal input from the driver and allow for more efficient operation and coordination, have shown significant potential for decreased fuel/energy consumption. While the information, awareness, and capabilities attributed to these automation systems offer many potential strategies for efficient operation, the sensors, processing and actuation components required by these systems represent a new additional power load which can reduce or cancel out the benefits provided by these new eco-capabilities. In addition to a sensitivity analysis of current vehicles to accessory loads, this work focused on evaluating the loads associated with two automation systems (a production Cadillac CT6 with SuperCruise and an industrial partner-supplied CAV prototype platform based on a Ford Fusion hybrid) under real-world operating conditions using on-road field testing of instrumented vehicles. While not exhaustive, this work utilized experimental data to identify trends, insights, and conclusions about the loads associated with automation systems and their impact on overall vehicle system efficiency.

Freeway driving with Super Cruise system enabled resulted in an overall average measured automation-related power consumption of 101 W to 104 W. The sensors themselves consumed an average of 52 W, or roughly 50% of the total system load. The engine control units (ECUs) and processing supporting the specific advanced driver-assistance systems (ADAS) features under review consumed 35 W, roughly 35% of the total consumption. The actuators (electric power steering and braking) consumed an average of 14 W over the course of testing. The consumption results were consistent regardless of environment or complexity of the driving situation. Surprisingly, the electrical loads of the vehicle's ADAS related sensors and processing changed minimally when Super Cruise was deactivated. This is likely due to the processing system and sensors being used for other safety and convenience features even during normal operation, suggesting that for lower level automation capabilities, the true accessory load penalty for certain eco-behaviors may be minimal if these systems are already in use for safer driving.

The CAV prototype vehicle was evaluated across two types of operation: 1) Highway Pilot, which allowed for hands-free highway operation requiring minimal driver attentiveness (similar to SAE L3), and 2) Urban Pilot, which allowed for driverless operation and navigation at lower speeds (similar to SAE L4). As shown in Figure 6, the overall automation system for the demonstrator vehicle consumed 315 W during Highway Pilot operation and 380 W during Urban Pilot operation. Also noteworthy is the processing loads of 236 W and 257 W for Highway and Urban pilot assist respectively, a significant increase from the processing loads for the Cadillac Super Cruise (35 W). In contrast to the Super Cruise results, the processing loads now represent 70% to 75% of the overall automation system automation loads, providing support for the hypothesis that processing loads related to higher automation levels are responsible for the large in-field electrical loads seen in recent pilots (although loads for this testing are still well under the reported 2-4 kW levels). Given the much higher processing power levels, it also stands to reason that these systems will likely need supplemental cooling, which is supported by the additional fan loads observed during testing, on the order of 19 W to 55 W depending on the use case and prior operating conditions.

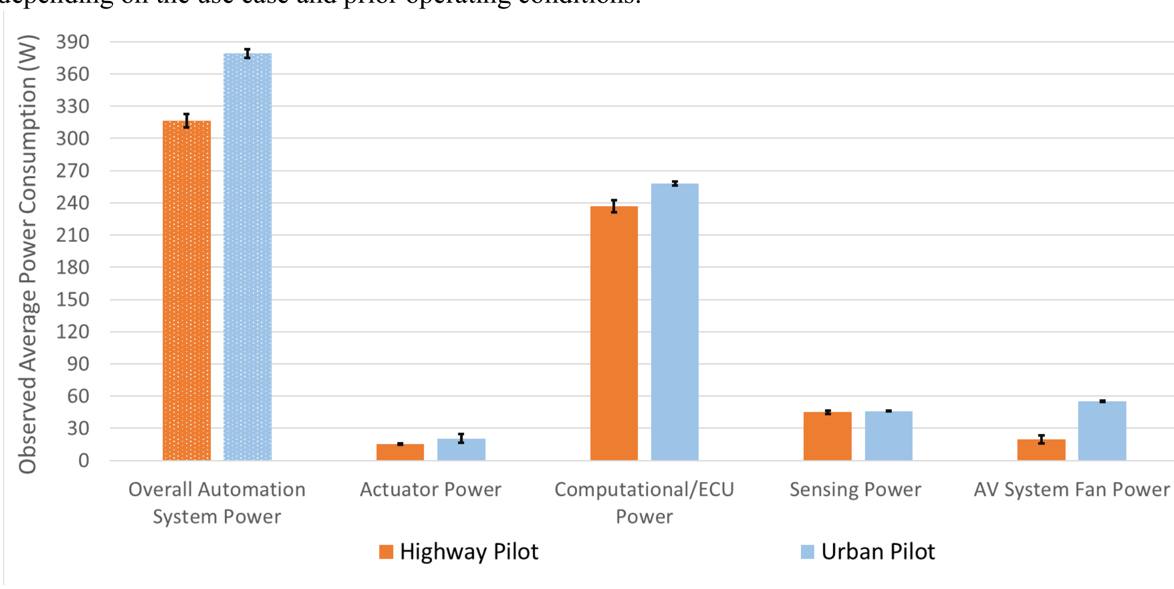

Figure 6. FEV Smart Demonstrator automation electrical loads during Highway Pilot and Urban Pilot operation on public roads (95% confidence interval shown in error bars).

While the 2-4 kW electrical loads observed in recent in-field AV trials may seem overly high based on this work, this report does not recommend applying the prototype vehicle's much lower consumption loads across the board to represent driverless systems capable of operating across a much wider set of operational design domains (ODDs). In fact, in consultation with several industry experts, a contrary opinion arose that, for driverless systems capable of operating across a wide range of ODDs, the 2kW and above processing loads may not begin to decline as quickly as many think. This is in part due to a continued need for higher resolution imaging/processing systems and a general need for more sensors for highly detailed situational awareness. In addition, the frame rate at which this information needs to be acquired and processed contributes to elevated processing loads, as electrical load can be estimated as proportional to calculations or operations per second.

CAV-Specific Modeling and Simulation Methodology and Approach Refinements

In order to evaluate new transportation technologies such as connectivity, automation, sharing, and electrification at different levels of fidelity and scale (i.e., individual vehicles to entire metropolitan areas) multiple approaches and simulations were refined to comprehend the complex dynamic interactions and capabilities of CAV technologies. These refinements built upon DOE's existing core capabilities related to advanced vehicle modeling and analysis. The specific CAV-centric modeling adaptations and evolutions developed in this effort included:

- An environment for simulating and optimizing the controls of multiple proximate vehicles with full powertrain control while comprehending and incorporating (when applicable) the interactions between these vehicles and their environment (RoadRunner)
- Improvements to traffic micro-simulation modeling tools to incorporate mixed fleets of manually and automatically driven vehicles within a particular traffic scenario or environment
- CAV-specific refinements to regional-level modeling tools relating to traffic flow models, representation of vehicle agents, and implementation of resource allocation and optimization routines related to specific CAV technologies and capabilities.

Corridor-to-Regional-to-National Level Impacts and Sensitivities of Connectivity and Automation

These efforts address the second research question of this work: "What are the GHG, energy, technology, and usage implications of connectivity, automation, and the combination of both technologies?" There is significant uncertainty regarding the expected outcomes of widespread CAV introduction into today's transportation systems and the dynamics of newly automated and/or connected vehicles operating in parallel with manually driven vehicles. These uncertainties lead to widely varying expectations for both the benefits and challenges associated with CAV introduction. The sensitivities and key assumptions of these expected impacts are also not widely established or documented. This work sought to fill these knowledge gaps with research focusing on the impacts of CAVs when introduced into current and near-term transportation systems, as well as develop tools and insights for future CAV deployment and transition dynamics and aggregation of results into a national-level impact assessment.

Corridor Level Impacts of Connectivity and Automation

- In contrast to the experimentally observed individual-level fuel savings benefits for ACC systems, corridor-level microsimulation modeling work done by the CAVs pillar showed that ACC systems decrease traffic throughput and increase overall energy consumption due to traffic instabilities created by the autonomously operating automation systems and the required following behaviors and distances associated with a lack of information from surrounding vehicles. At 100% ACC market penetration, fuel consumption within the study corridor increased by up to 60%. Contrasting these impacts, Cooperative-ACC (CACC), ACC enhanced by vehicle-to-vehicle (V2V) communications, showed benefits to both congestion and consumption as market penetration increased above 40% and may ultimately remove traffic congestion at current demand levels with sufficient penetration. At penetrations lower than 40% CACC acted much like an ACC system; thus, without additional considerations or technologies, low penetrations of CACC vehicles will also lead to decreased throughput and increased consumption at the corridor level.

To compare the impact of ACC (as a proxy for automation without connectivity) and CACC (a case of automation combined with connectivity) at different penetration levels on traffic within a corridor, the same calibrated baseline traffic car-following model was used for both cases. The models were calibrated with field-collected data from several ACC and CACC vehicles driven in public traffic. These car-following models are intended to capture the dynamic interactions between manually driven vehicles and ACC and CACC vehicles.

The combined figure below illustrates the contrast between the trends in achievable throughput per lane as the market penetration increases for (unconnected) ACC (left plot) and cooperative ACC (right plot) systems. The simulation scenario for these results was a section of four-lane freeway operating at its maximum achievable upstream throughput level, with a single exit ramp serving different exiting traffic volumes, ranging from 0% (the ideal case) to 25% of the mainline volume. The decline in achievable downstream throughput with increasing use of ACC is in distinct contrast to the increase in downstream throughput with increasing use of CACC. This occurs because the ACC destabilizes the vehicle-following control while the CACC stabilizes it and enables vehicles to be driven at shorter gaps due to the connectivity and information shared between vehicles.

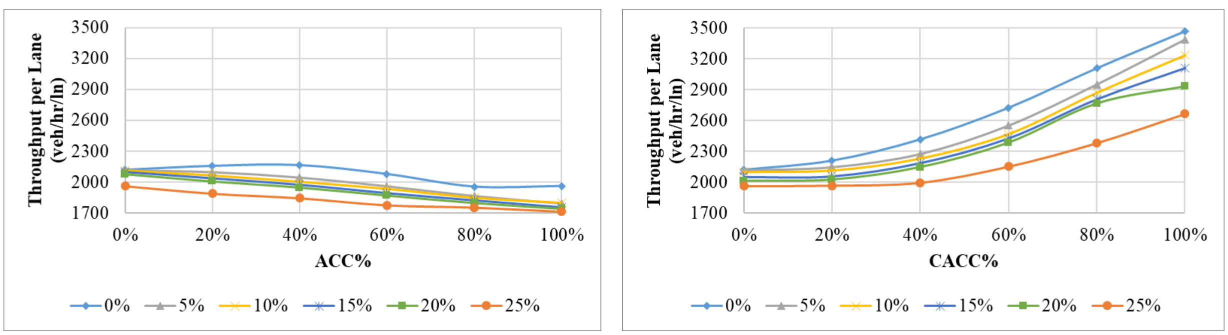

Figure 7. Corridor throughput versus ACC penetration level (left) and CACC penetration (right); the color codes represent the percent flow through the off-ramp with respect to the mainline volume.

The effects of ACC and CACC on energy consumption can be visualized more clearly on contour plots for this simple scenario (the four-lane freeway section with a single on-ramp). The contour plot below shows fuel consumption for a 13.5 km corridor for one hour of operation. The vertical axis of each plot represents the location along the freeway, the horizontal scale represents the time, and the colors represent the traffic speeds. The results show that when all vehicles are using CACC, the impact of the on-ramp traffic is negligible, in contrast to when all vehicles are using “autonomous” ACC. In the latter case the fuel consumption increases significantly because of unstable vehicle following.

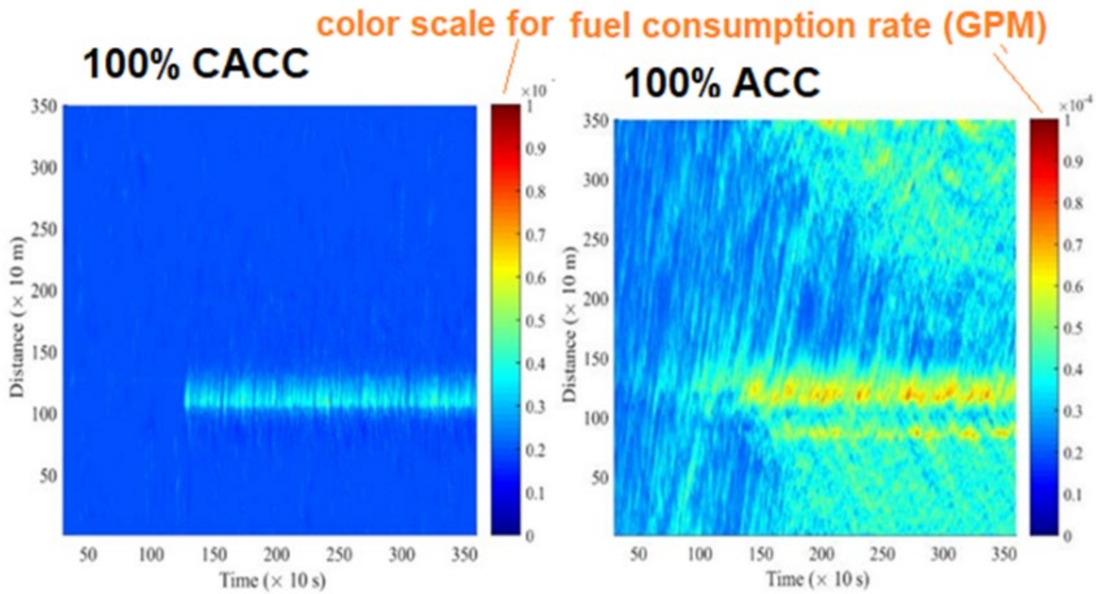

Figure 8. Fuel consumption rate (GPM - gallon per mile travelled) contour plot for 100% CACC driving (left) and 100% ACC driving (right) in response to a traffic disturbance caused by an on-ramp.

Regional-Level Impacts of Connectivity and Automation

- Regional-level modeling results for Bloomington, Il-based simulation and analysis done by the CAVs pillar have shown that by inducing additional travel demand and facilitating zero-occupancy vehicle (ZOV) travel, privately owned, driverless-capable automated vehicles have the potential to increase regional-level vehicle miles traveled (VMT) by 42%–63%. This increase in VMT can offset nearly all future vehicle efficiency improvements within the DOE's 2040 technology portfolio, resulting in a 50%–70% increase in total energy consumed versus a future scenario without the introduction of privately owned, driverless-capable automated vehicles.

In the long term, fully automated, privately owned vehicles have the potential to substantially impact traffic and energy use by two factors: increased travel and zero occupancy vehicle (ZOV) capability. Using agent-based modeling tools developed and refined in this effort, researchers conducted a case study investigating the impacts of privately owned (shared across household members) CAVs in the Bloomington, IL metropolitan area. The study employed a range of estimated CAV and powertrain technology demand scenarios, spanning 2015 to 2040. Each model year assessed within the study included baseline, low, and high CAV penetration scenarios (determined by assumed marginal price of the CAV), low and high advanced vehicle powertrain adoption scenarios, and three CAV technology design scenarios related to automation electrical loads, market penetration of CAVs, and disincentives for ZOV operation. For 2040, the impact of two ZOV pricing scenarios was also assessed. The model results highlight the substantial impact on vehicle travel and energy consumption from increasing automation. The results indicate that the presence of a significant penetration of fully automated privately owned vehicles would induce a 27% to 39% increase in trips depending on penetration rate and cost. Combined with the effect of ZOV travel, this would increase system level VMT by 42% to 63%. When analyzing the energy consumption driven by this increase in VMT, overall fuel consumed across the 2015 to 2040 timeline could increase by 50%–70%, possibly negating most of the gains in reduced fuel consumption due to improvements in vehicle powertrain technology over time.

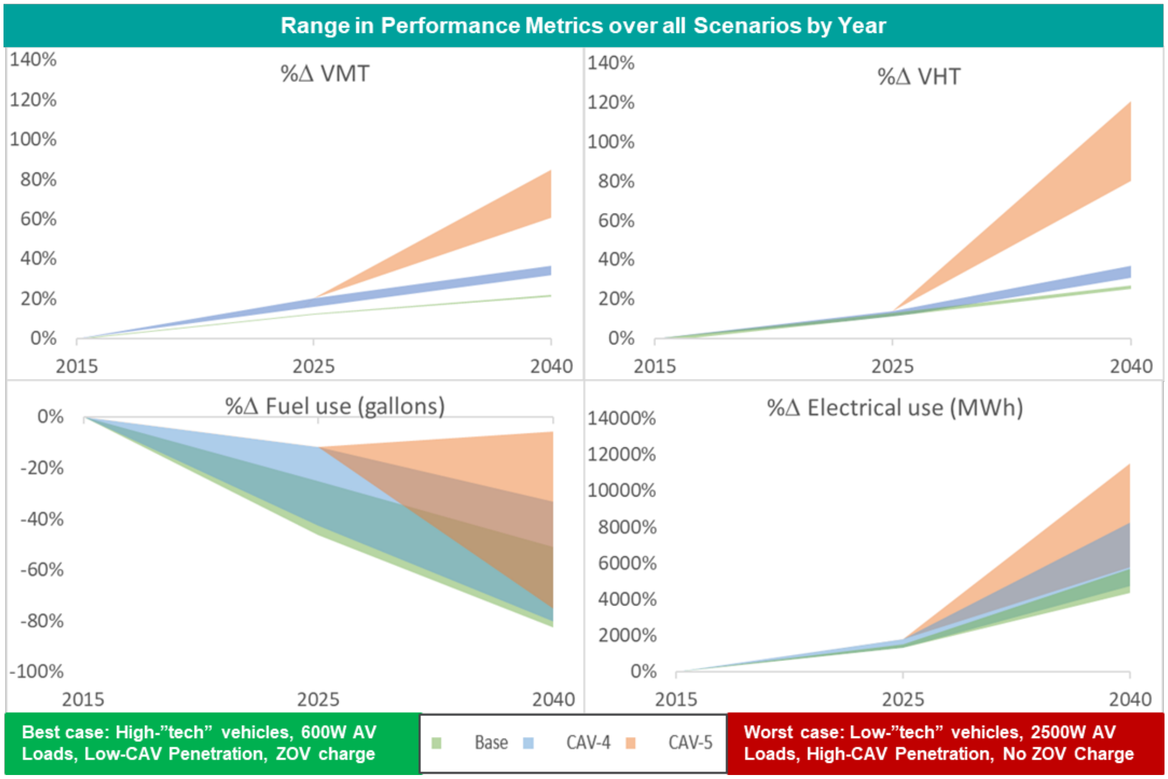

Figure 9. Best and worst case performance metrics over time under privately owned, Level 4/5 CAV scenarios.

National Level Impacts and Aggregation Techniques for CAV Behaviors and Technologies

CAVs may significantly alter mobility, change the utility of travel, and result in large changes in transportation energy use. In SMART Mobility and related research efforts, these potential changes were studied using models and simulations, largely at a regional or local scale. The CAVs Pillar also explored methodologies for synthesizing regional, local, and vehicle-level results to a national level. The approach applied was split into three sections: methodologies to estimate changes in travel demand, techniques to aggregate vehicle fuel consumption, and insights into CAV technology adoption. The goal was to take results from regional simulations, vehicle simulations, and estimated market penetrations of CAVs and other vehicle technologies to calculate CAV related impacts and energy use under various national-level scenarios. The results provided fuel consumption aggregation techniques and CAV adoption projections that were used in other SMART Mobility tasks and provided insights into methods for modeling changes in travel behavior at the national level due to CAVs. Specific methodology highlights and findings from these efforts include:

- Extrapolating the results of detailed, activity-based, transportation system simulations to other locations or other populations is challenging, especially for travel metrics such as VMT, since VMT depends not only on traveler characteristics but also on road network characteristics and other land use characteristics at local and regional geographic scales
- Individual road-link and metropolitan-area energy consumption estimation roll-up techniques can also be successfully applied for national-level energy consumption estimates under a range of different scenarios
- Highly automated vehicles are expected to become a large portion of projected future personal and/or shared-mobility fleet vehicle sales, given that they offer significant consumer benefits, including reduced travel time costs through more productive use of travel time, as enabled by a reliable automation system

- In addition to reduced travel time costs, highly automated vehicles are also valuable for limited-range BEVs, since the gain in energy efficiency (due to more efficient vehicle driving dynamics and routing) results in valuable extended range and reduced range anxiety
- Highly automated vehicles may increase personal vehicle ownership if first adopted as personal vehicles or decrease personal vehicle ownership if they are first adopted as shared TNC vehicles at a significant scale.

Harnessing Connectivity and Automation for Improved Energy Outcomes and Coordination

Results discussed in this section worked to address the third research question posed in these efforts: "What is the best way to harness CAVs for reduced energy use and improved mobility in transportation?" Efforts in this section focused directly on the new control and coordination capabilities afforded to CAVs through improved situational awareness, controllability, automation, and connectivity. Results from this research quantify the possible traffic flow and efficiency benefits of CAVs in multiple scenarios for an individual vehicle, corridor, region, or city, including sensitivities due to different penetration levels and varying degrees of automation. Broadly speaking, this section seeks to investigate how one can combine driver feedback systems, improved controls, situational awareness, and other strategies to better control connected, non-automated vehicles as well as connected and automated vehicles for less energy intensive and higher roadway throughput outcomes.

Eco-Driving: Energy-Focused CAV Control Development Using Powertrain and Longitudinal Speed Control

- By adapting to the road, surrounding vehicles, and the green/red sequencing of traffic lights, SMART Mobility consortium researchers developed control algorithms for individual automated vehicles with intelligent powertrain and speed control. These algorithms can reduce energy/fuel consumption up to 15% alone, and up to 22% when integrated with Vehicle-to-Infrastructure communication of traffic signal information. Large-scale simulation studies applying the algorithms have shown these benefits vary significantly depending on scenario and powertrain technology, with BEVs showing up to 7% reduction in consumption.

A single vehicle intelligent powertrain and speed control algorithm developed by the SMART Mobility Consortium was shown to reduce energy consumption up to 22% (depending on powertrain and road type) in real-world driving conditions by adapting to the road topography, surrounding vehicles, and the sequencing of traffic lights. Energy savings vary significantly depending on the scenario:

- Eco-driving saves more in city driving (up to 22%) than in highway driving (up to 6%)
- *Speed+powertrain* eco-driving often saves more than the *speed-only* eco-driving, between 4 and 9 percentage points more, by considering the best operating points for a specific powertrain. For example, the *speed+powertrain* strategy enables the engine to operate at more efficient loads through stronger accelerations, resulting in 2 percentage points higher average engine efficiency.
- V2I-enabled traffic light eco-approach increases eco-driving energy savings, especially for speed-only eco-driving (up to 10 percentage points more relative to non-connected vehicles).
- While energy savings are greater for the lead vehicle than for a following vehicle without eco-driving controls, non-equipped vehicles can also reduce their energy consumption up to 8% when they follow a vehicle equipped with eco-driving.
- Combined with technologies to increase engine efficiency at low loads (2025 VTO targeted efficiency goals), the developed eco-driving strategies show up to 6 extra percentage points of energy consumption savings for the 2025 target compared to the current baseline.

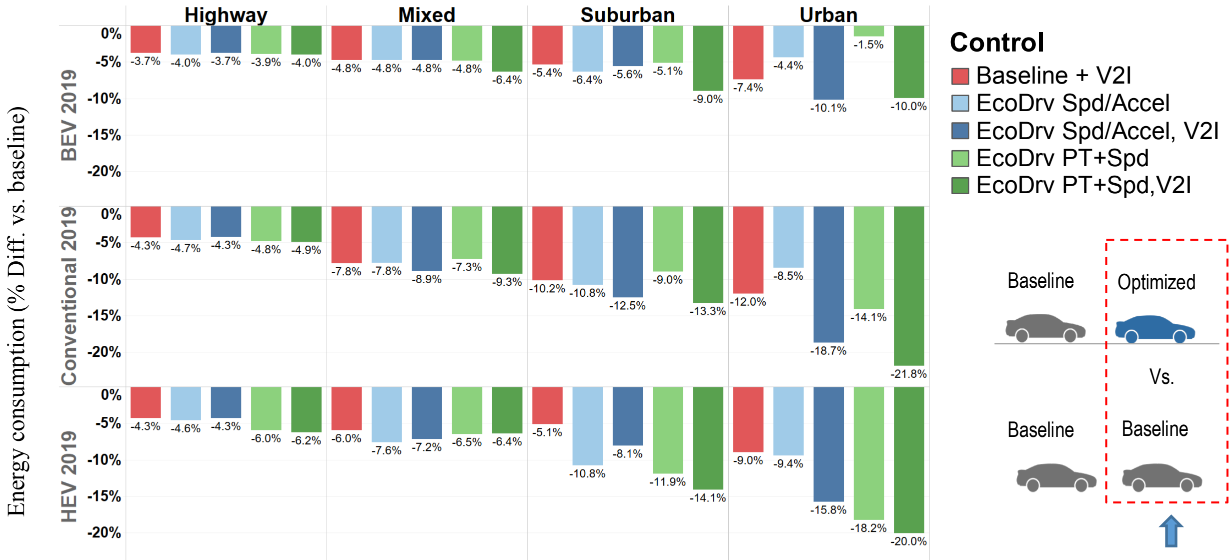

Figure 10. Energy consumption savings compared to baseline control for a vehicle in the lead position, with current powertrain technology, for various powertrains.

The control algorithms were developed using RoadRunner, a new simulation tool for energy-aware CAV control development. Multiple scenarios were considered to quantify the energy impact, including:

- A large number of real-world routes covering different terrain and road types (highway, suburban, urban only and mixed)
- Multiple vehicle powertrains (conventional engine-powered vehicle, hybrid electric vehicle, and battery electric vehicle) along with two component technology scenarios (current term scenario, and the short-term future "high" case representing 2025 U.S. DOE VTO technical targets)
- Two types of eco-driving controllers: EcoDrv Spd/Accel, which optimizes vehicle speed vehicle independently of the powertrain, and EcoDrv PT+Spd) which optimizes vehicle speed and powertrain simultaneously. Both controllers can utilize V2I information to receive traffic light signal information.

Active Traffic Management Strategies for Corridor-Level Traffic Improvements

- Corridor-level simulations done by the CAVs Pillar showed that overall corridor traffic throughput improvements are possible when vehicles with automated longitudinal controls (i.e. ACC) are equipped with supplementary vehicle-to-infrastructure (V2I) communication capabilities allowing them to follow variable speed limit/advisories (VSL/VSA) broadcast within the corridor and be responsive to dynamic traffic conditions. For penetrations of 10-30% ACC+V2I equipped vehicles within the simulated corridor the following improvements were observed:
    - Total travel time (TTT) could be reduced by 6-7%
    - Speed variation could be reduced by 8%
    - Total delay could be reduced by 9-11%.

As discussed in this report and several other studies, an increase in ACC market penetration (i.e., automated but non-connected vehicles) can aggravate traffic and lead to more energy consumption since ACC, as a longitudinal autonomous driving mode, has inferior performance compared to experienced drivers when following vehicles. Although CAVs (with V2V) can effectively avoid these deficiencies and improve traffic mobility and safety, low market penetration of CAVs will not bring many opportunities for CACC/platooning capable vehicles to create strings in the near-term. Therefore, most CAVs will have to be operated in an autonomous only mode until there is a higher penetration of CAVs enabled with CACC. In this context, our investigation was intended to improve traffic mobility, safety, and energy consumption using V2I based information. The results showed that although ACC will have longer (time) gaps between vehicles, which is detrimental to traffic, V2I types of VSL/VSA could compensate for this by increasing overall performance at the system level.

The investigative approach adopted a VSL strategy to optimize the downstream bottleneck flow within the study corridor. It was assumed that all the automated or partially automated vehicles operating in the study corridor have vehicle-to-infrastructure connectivity, but not vehicle-to-vehicle connections. With these V2I connections, the VSL determined by the traffic management center (TMC) can be passed to the vehicles and used as the set-speed of the vehicle's ACC system, or be displayed to the driver, via connectivity. For evaluation and development of the proposed algorithms, a well-calibrated Aimsun microscopic traffic simulation model of eastbound I-66 inside the Washington D.C. beltway was used.

Table 1 shows the percentage change in mobility performance metrics, compared to the baseline traffic, for the developed algorithms applied to the study corridor. Numbers in green indicate traffic improvement and numbers in red indicate traffic deterioration. The results of the DC corridor study showed an improvement in all mobility metrics (total travel time [TTT], total travel distance [TTD], total delay [TD], speed variation, number of stops) even with 10% penetration of ACC vehicles, and confirm the benefits of improved traffic through V2I-based VSL guidance, even for relatively low penetrations of ACC or CACC vehicles. This approach uses currently available road traffic detector information and vehicle longitudinal control capabilities (supplemented with V2I communications) to calculate, provide, and follow VSL guidance for small sections of the freeway corridor, showing promise to improve traffic even when the penetration of CAVs is low.

Table 1. Averaged performance parameter improvements for each penetration level of ACC vehicles over 10 replications.

Market Penetration	TTT (%)	TTD (%)	TD (%)	Spd. Var. (%)	Ave. # of Stops (%)	Flow@Syc. (%)	Flow@ Merge (%)
10%	-6.0	0.8	-9.4	-8.4	-3.5	1.8	-0.2
30%	-7.0	1.3	-11.0	-8.3	-4.2	2.4	-0.1
50%	-8.9	1.4	-13.7	-9.3	-4.9	2.2	-0.1
Mean	-7.3	1.2	-11.4	-8.7	-4.2	2.1	-0.1

CAV-Enabled Optimal Coordination Strategies and Impacts for Highlighted Traffic Scenarios

The CAVs pillar developed an optimization and simulation framework to optimally coordinate CAVs across a range of traffic scenarios and varying penetration levels of automated and manually driven vehicles showed significant opportunities for reduced congestion and reduced corridor-level energy consumption. Highlighted benefits include:

- With partial penetration of CAVs and a heterogeneous fleet (different vehicle classes from light-duty to heavy duty), the optimal coordination framework developed by the SMART Consortium can provide fuel savings of 3% to 30% for a highlighted freeway merging scenario under moderate to heavy traffic.
- With full penetration of CAVs, the optimal coordination framework developed by the SMART Consortium, enables the vehicles crossing a roundabout to save up to 27% of fuel and between 3% and 49% of travel time depending on the traffic conditions.
- In a simplified highway corridor at full penetration of CAVs, the developed optimal coordination strategy mitigates traffic jam propagation, leading to travel time savings of up to 40% and improvements in fuel economy of up to 55% compared to the non-coordinated scenario.

- For a longer, real-world corridor, even at lower CAV penetration levels, the developed coordination framework still achieves a significant overall corridor fuel consumption reduction. For example, at 20% CAV penetration, a benefit of 4% is achieved.

Much of the current research related to control and coordination of CAVs (external to DOE efforts) has been focused on safety and travel time. Several studies have attempted to quantify the energy implications of proposed control and coordination strategies considering full penetration of CAVs, however, the implications of partial penetration of CAVs on energy and travel time have been an under-explored aspect within the research community. The CAVs Pillar explored the impacts of an optimal coordination framework for CAVs in the presence and absence of interactions with human-driven vehicles, i.e., considering partial and full penetration rates of optimally coordinated CAVs under different traffic conditions. The main focus areas of this work are: 1) the development and expansion of a simulation framework to capture the interaction of CAVs with human-driven vehicles under different traffic volumes for a range of traffic scenarios, and 2) the analysis of the impact that different penetrations of CAVs have on fuel consumption, travel time and traffic flow when the optimal coordination framework is applied. While this work assessed a wide range of traffic scenarios and CAV penetration scenarios, key insights include the following.

Vehicle Merging at a Highway On-Ramp — Mixed Penetration of CAVs

With partial penetration of CAVs and a heterogeneous fleet (i.e., different vehicle classes from light-duty to heavy duty), the optimal coordination framework for CAV merging developed by the SMART Consortium can provide 3% to 30% fuel savings for a freeway merging scenario under moderate to heavy traffic. The results in the figure below show that the benefits are sensitive to traffic demand. The higher benefits in terms of average fuel consumption savings occur in scenarios with moderate congestion (e.g., 2000 veh/h) since the vehicles will still have some freedom to accelerate and decelerate in an optimal way. At lower traffic demands (e.g., 1800 veh/h), the reduced traffic on the main road allows more human drivers to merge without conflicts in the baseline scenario, avoiding significant acceleration/deceleration changes. This results in smoother travel patterns than in moderate baseline traffic and thus reduced opportunities for improvement via optimal coordination. However, the fuel saving benefits at lower traffic volumes still exceed 10%. In heavy traffic, the vehicles are more constrained in their responses due to the smaller headways, and the idling condition starts dominating, reducing the potential to save fuel and improve the average fuel economy. Still, the average fuel savings in heavier traffic vary between 2% and 17%. Notably, at lower penetration rates for all the simulated traffic demands, there is increased uncertainty and performance variability regarding the fuel consumption savings. This result suggests that low market penetration scenarios will probably also see higher variability in performance in the real world as well. As CAV penetration increases, more vehicles will attempt to communicate and merge in a coordinated way; however, they will still be constrained by the unknown behavior of human drivers and the lack of accurate information about their decisions and intentions. In these mixed partial penetration scenarios, CAVs need to rely on their own estimations (through sensors) to ensure collision-free trajectories. Thus, CAV efficiency will be adversely affected by non-smooth and often unpredictable human-driven vehicles when attempting to merge, and they will be required to perform harder accelerations/decelerations and stopping maneuvers to ensure safety, which will affect downstream traffic. These erratic maneuvers result in the variable fuel consumption trends observed in the figure below.

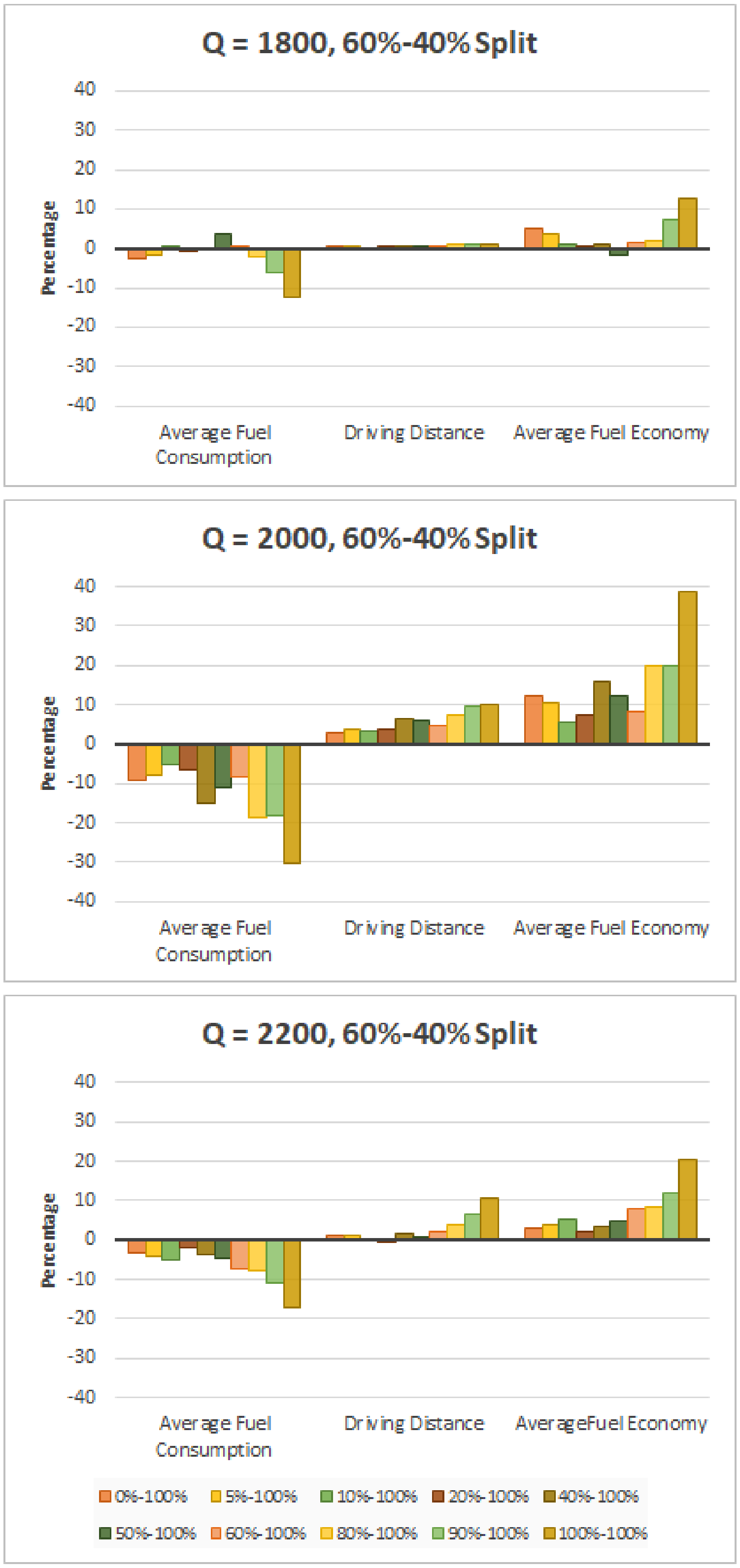

Figure 11. Average fuel consumption, driving distance, and fuel economy with respect to baseline for three traffic demands, i.e., 1800 veh/h, 2000 veh/h and 2200 veh/h (60% - 40% split between the main and ramp roads) with various CAVs market penetration rates (numbers in the legend identify the percentage of light-duty CAVs and the percentages of heavy duty CAVs respectively).

Roundabout Coordination — Full Penetration of CAVs

With full penetration of CAVs, the optimal coordination framework for roundabout coordination enables the vehicles passing through a roundabout to reduce fuel consumption up to 27% fuel and travel time between 3% and 49%, depending on the traffic conditions. This work simulated a simple roundabout network in two scenarios: 1) a network with 0% CAVs penetration (baseline), and 2) a network with 100% CAVs penetration. In addition to the penetration scenarios, to test control effectiveness under different traffic conditions, east and west entry volumes varied from 300 veh/h to 1000 veh/h. At low traffic volumes, the headways between westbound vehicles were generally large enough that few eastbound vehicles needed to stop to get into the roundabout. In the baseline scenario, as entry volume increased, it was harder for eastbound traffic to find proper gaps into which to merge, resulting in a queue buildup. With the proposed control algorithm, the network throughput was improved, and the eastbound vehicles were able to merge into the roundabout without stopping, even with high circulating flow. Therefore, the total number of vehicles exiting the roundabout in a given time period increases, leading to improved roundabout capacity (e.g., 25% improvement with 1000 veh/h per lane entry volume) as well as reduced travel times due to the lack of queue buildup. By eliminating stop-and-go driving for eastbound traffic, vehicle transients are minimized, leading to direct fuel consumption savings of roughly 27%.

Simple Highway Corridor — Full Penetration of CAVs

For a simplified highway corridor, at full penetration of CAVs, the developed optimal coordination mitigates traffic jam propagation, leading to travel time savings of up to 40% and improvements in fuel economy of up to 55% over the non-coordinated scenario. The effectiveness of the proposed optimal coordination framework was assessed on a simplified highway corridor (length 2.5 km) with two on-ramps and one off-ramp. The optimal coordination framework was implemented and simulated for the corridor at 0% (baseline) and 100% (optimal) CAVs market penetration. By following the optimal control inputs, the vehicles followed smoother acceleration patterns and avoided stop-and-go driving commonly observed in the baseline scenarios when the on-ramp vehicles attempted to merge onto the main road.

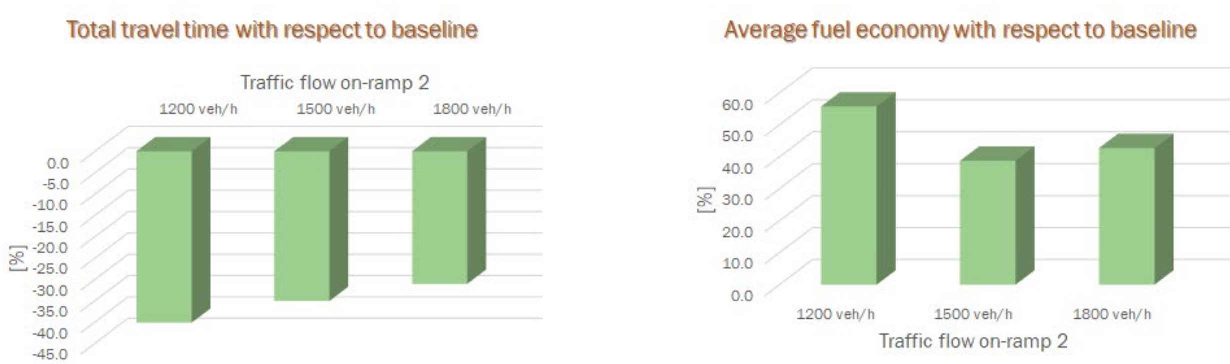

Figure 12. Average fuel economy and travel time results for the simulated highway corridor (2.5 km).

Optimal Coordination for a Real-World Corridor Segment (I75 Corridor) — Mixed Penetration of CAVs

In a longer real-world corridor, at lower CAV penetration levels, the developed coordination framework still achieved significant overall corridor fuel consumption savings for a range of mixed traffic scenarios (all heavy-duty vehicles were assumed to be automated for all scenarios). For example, at 20% light-duty CAV penetration, a benefit of 4% was achieved. As can be seen in the figure below, the fuel savings trend increased steadily with increased light-duty CAV penetration when more than 10% of the vehicles on the road were CAVs, and reached a maximum of about 7% at full CAV penetration (i.e., 100% CAVs).

Table 2. Market penetration rates considered for longer real-world corridor assessment.

Scenario:	Base	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
% Light-Duty CAVs	0	0	5	10	20	50	80	100
% Heavy-Duty CAVs	0	100	100	100	100	100	100	100

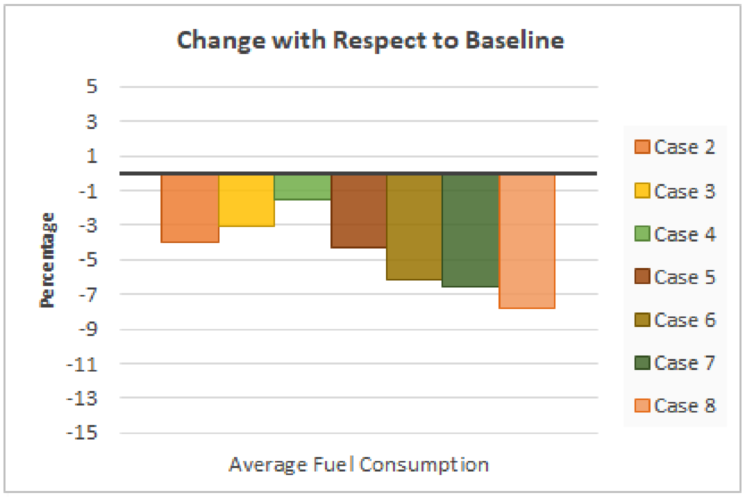

Figure 13. Fuel consumption results for longer real-world corridor assessment.

Regional Level Strategies for CAV Impact Mitigation

- CAVs Pillar modeling results from Bloomington- and Chicago-based studies have shown that fleets of shared, ride-hailing based (versus privately owned) automated vehicles have the potential to reduce zero occupancy miles, mitigating some of the increased VMT and energy consumption impacts due to certain CAVs technologies. In addition to the vehicle-level and corridor-level consumption and congestion reduction strategies discussed above, other promising regional-level mitigation strategies identified included low-cost TNC access to transit and zero occupancy vehicle pricing optimization.

As discussed earlier, high levels of vehicle automation can possibly lead to elevated overall energy consumption within a region due to significantly elevated VMT and possibly more congestion due to the overall number of additional trips facilitated by automation. This section seeks to highlight some of the regional level strategies investigated to mitigate some of the less desirable aspects of certain future highly automated vehicle use cases. The study results shown below are not intended to cover all possible mitigation strategies, rather highlight some of the promising options uncovered and evaluated within these efforts.

Impacts of Automated SAVs on Energy and VMT

Given the dramatic impacts that privately owned automated vehicles were observed to produce, especially the possibility of increased energy use as well as significantly increased VMT and VHT, one additional possibility considered in this research is the use of shared automated vehicles (SAVs), i.e., automated vehicles operated by TNCs. A case study, highlighted in this document and discussed in much greater detail in the companion SMART Mobility Modeling Workflow Capstone Report, was performed using the POLARIS model of Chicago that, among other scenarios, investigated the impacts of ride-hailing versus privately owned fully automated vehicles. While only the highlights of the results are presented in this document, this work shows some important considerations and impacts related to ride-hailing and privately owned fleets of highly automated vehicles. Specifically, due to zero occupancy miles, privately owned automated vehicles are much less efficient, on an energy use per traveler mile basis, than shared fleets of automated vehicles.

Many of the relevant issues leading to this lack of efficiency can be observed in the figure below, which compares a scenario with high ride-hailing use and no private AVs to a scenario with high private AV ownership and low ride-hailing usage for the Chicago area. While both scenarios see significant use of shared vehicle assets (i.e., ride-hailing/SAV usage in the shared fleet case and intra-household AV sharing in the privately owned case), there are still significant advantages to be had through usage of ride-hail fleets of automated vehicles. ZOV trips for personally owned vehicles related to repositioning and other behaviors lead to a significant increase in overall travel, as these vehicles do not achieve the higher efficiencies associated with larger-scale ride-hailing SAV automation, which allows for more productive use of the vehicle assets (less empty travel). Compared with the Chicago metropolitan region baseline case for this study, a significant (52%) penetration of privately owned AVs would lead to a 42% increase in VMT, a 62% increase in VHT, and a 12% decrease in average vehicle travel speed.

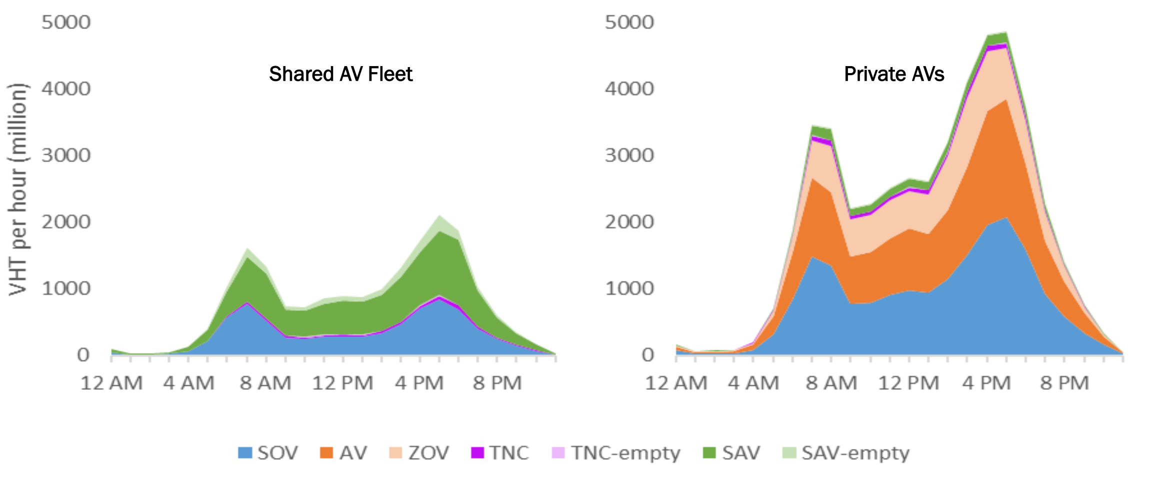

Figure 14. Private AV vs. shared AV million travel hours per hour.

Low-Cost TNC Access to Transit

This work investigated into the impacts of providing very low/no cost ride-hailing trips to public transit stops/terminals to help facilitate transit access for travelers. Utilizing Bloomington, Illinois and its metropolitan area, this study investigated the regional changes when ride-hailing drop-offs at bus stops were provided at zero cost. In this scenario, overall transit ridership increased by 11% with a resulting 1.4% decrease in overall VMT and a 1.1% decrease in overall fuel use, suggesting that providing low cost transit access (likely enabled by CAV technologies) can provide some regional benefits relative to overall energy use. Additionally, these near-free transit-access rides appear to offer some travelers in outlying regions increased access to transit, with additional benefits related to overall productivity and access to jobs.

Zero Occupancy Vehicle Pricing

Given that zero occupancy vehicle (ZOV) operation was found to be one of the primary drivers of the elevated VMT in several of the highly automated future scenarios investigated for this work, a strategy of pricing zero occupancy vehicle miles traveled was investigated as a possible lever to reduce some of the increased VMT. The study, again based in Bloomington, Il., showed that depending on the penetration of AVs, a $0.33/mile ZOV charge showed a very significant—approximately 25%—reduction in ZOV miles traveled for both high (65%) and low (37%) AV penetration scenarios run for the Bloomington study. This ZOV VMT reduction corresponds to an overall reduction in VMT of up to 4%.

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1 Introduction

The U.S. Department of Energy's Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium is a multi-year, multi-laboratory collaborative dedicated to further understanding the energy implications and opportunities of advanced mobility technologies and services. The SMART Mobility Consortium consists of five pillars of research:

- Connected and Automated Vehicles (CAVs): Identifying the energy, technology, and usage implications of connectivity and automation and identifying efficient CAV solutions.
- Mobility Decision Science (MDS): Understanding the human role in the mobility system, including travel decision-making and technology adoption in the context of future mobility.
- Multi-Modal Freight (MMF): Evaluating the evolution of freight movement and understanding the impacts of new modes for long-distance goods transport and last-mile package delivery.
- Urban Science (US): Understanding the linkages between transportation networks and the built environment and identifying the potential to enhance access to economic opportunity.
- Advanced Fueling Infrastructure (AFI): Understanding the costs, benefits, and requirements for fueling/charging infrastructure to support energy-efficient future mobility systems.

The SMART Mobility Consortium creates tools and generates knowledge about how future mobility systems may evolve and identifies ways to improve their mobility energy productivity (MEP).[i] The consortium also identifies R&D gaps that the Energy Efficient Mobility Systems (EEMS) Program may address through its advanced research portfolio and generates insights that will be shared with mobility stakeholders.

1.1 Overview of Connected and Automated Vehicle Technologies, Use Cases, and External Influences

The continued growth of CAV technologies is anticipated to significantly change the way vehicles move and the way travelers achieve mobility. This will have a significant impact on energy consumption as well as many other facets of transportation at scales ranging from the individual vehicle level to the system level. CAV technologies are unique in that they can positively *and* negatively impact efficiency (both energy efficiency and passenger/freight efficiency) as well as vehicle miles traveled (VMT) and related metrics. Additionally, due to interactions between connectivity/automation enabled technologies and the particular powertrain technology onto which it is applied, the benefits of a particular technology (CAV or powertrain) will increase or decrease due to synergies between the new operating profile and the specific powertrain under analysis. For example, the benefits of regenerative braking are decreased in an environment where most vehicle transients are removed through improved vehicle cooperation and profile smoothing.

CAV technologies are highly diverse, and disaggregating this broad spectrum of technologies into specific system operating concepts is often helpful in framing a more detailed research and analysis discussion. Based on the discussion in a research report developed under the SMART Consortium,[2] the following sub-sections define a limited number of discrete CAV concepts that represent a wide range of automation levels, connectivity and use cases. While not intended to be all-encompassing, the technologies and strategies discussed in the following sections will aid the reader in understanding the breadth and complexity of the connected and automated vehicle space.

1.1.1 Vehicle Connectivity Only (Without Automation)

Since connectivity features are generally independent, and their impacts are largely decoupled from each other, connectivity features can be treated as independent features that can be combined as desired. Within this

[i] MEP: A DOE-developed, multi-modal measure that quantifies the effectiveness of mobility in a region, while taking energy and affordability aspects into consideration.

discussion, connectivity may include vehicle-to-vehicle (V2V) communication, infrastructure-to-vehicle (I2V) communication, vehicle-to-infrastructure (V2I) communication, or generalized vehicle-to-anything (V2X) communication. Use cases include the following:

- *Cooperative collision warning systems (V2V, I2V)* — These systems use wireless communication to enable vehicles to broadcast information about their motion to all other vehicles and vulnerable road users. Trajectory information and other vital information about vehicle size and class can be used to predict potential collisions and to issue warnings to drivers to help them avoid crashes, injury and loss of life. Since crashes are responsible for about a quarter of the congestion on U.S. roadways, reductions in crashes could also help reduce the frequency and severity of congestion as well as the related wasted energy.
- *V2V cooperative driving/maneuvering enhancements* — One of the main triggers of traffic congestion on controlled access highways is lane changing maneuvers by drivers entering the highway from on-ramps, changing lanes at lane reduction locations, or engaging in weaving maneuvers to gain an expected travel time advantage or to get to the exit lane at a destination. Lane-changing drivers and the drivers of the other vehicles in their immediate vicinity have primitive ways of communicating their intentions and preferences today (hand gestures or turn signals, which are not always used), but with V2V communications those intentions can be displayed directly on the instrument panels of other drivers, and it becomes possible to negotiate cooperative maneuvers earlier and more smoothly than today, reducing some of the congestion disturbances and facilitating more efficient operation.
- *V2I/I2V route planning, parking information and reservations (eco-trip planning and routing) —* Drivers currently choose their routes based on limited knowledge about the road network and the traffic conditions between their origin and destination. More complete information about real-time traffic congestion, traffic signal phase and timing, and availability of parking can be provided using I2V communications so that drivers will be better able to avoid the worst traffic conditions, minimize their stops and idle times at red traffic signals, and find available parking spaces without excessive search time. With the addition of V2I communications, they can also request a reservation for a parking space based on a real-time anticipated arrival time to further reduce VMT waste in the search for parking spaces.
- *V2I/I2V based variable speed limit/advisory (VSL/VSA)* — V2I/I2V technology makes highway and arterial corridor traffic speed control more convenient and efficient by providing speed limit and other advisory information to vehicles and drivers. Enabled by connectivity, the connected vehicles behave like moving sensors, which can greatly enhance the traffic detection of roadside sensors, and roadside decisions such as variable speed limits/variable speed advisories (VSL/VSA) from the TMC (Traffic Management Center) can be passed to vehicles for the drivers to follow. This is particularly effective for mobility and safety improvement if the downstream traffic is congested.
- *Local Signal Phase and Timing (SPaT) information to support eco-driving and eco-signal control —* Traffic signals that broadcast their real-time SPaT information can help drivers save energy that would otherwise be wasted by excessive frequency and severity of stop-start cycles. Broadcasted SPaT data can be used by in-vehicle systems to display recommended speed changes, allowing drivers to get through a green signal before it turns red or to coast down to a slower speed approaching a red signal without stopping if that signal will soon be turning green. The V2I communications in the opposite direction can be used to generate signal priority requests or simply to inform the signal controller of the arrival of a vehicle that is waiting for a green phase (which could be provided with a minimum delay if other vehicles are not making a conflicting movement).

1.1.2 Vehicle Automation

These attributes are not generally independent because of their close coupling with each other, which makes it difficult to limit the dimensions of the alternatives that need to be considered. When several coupled variables influence the energy saving potential of an automated vehicle, it can be difficult to determine how much of that energy saving is attributable to each variable. The primary relevant attributes of automated vehicles that need to be considered are:

- *Connected vs. unconnected (autonomous) implementation* — This is one of the most important classification attributes for considering the energy impacts of any AV (automated vehicle) system, because the unconnected version of an AV could produce significant negative impacts while the connected version of the same AV could produce significant positive impacts. For example, the use of V2V information communicated from other vehicles makes it possible to reduce traffic flow disturbances and drive AVs closer together, with smoother speed profiles and reduced aerodynamic drag. Without V2V information, the gaps between AVs will likely have to be larger than current gaps, reducing roadway capacity, amplifying disturbances, and resulting in excess acceleration and braking cycles.
- *SAE levels of automation: Levels 0–5 (6 levels)* — The dominant characteristic used to distinguish among different automation systems is the level of automation, as defined by SAE J3016.[3] These levels specify the functionality that is implemented by the driving automation system and the functionality that is retained by the driver, regardless of the specific technological implementations that different manufacturers may choose (such as types of sensors or actuators). Simplified definitions are provided below:
    - *Level 0: No Driving Automation* — Safety warning or intermittent control intervention systems could be implemented at this level, since they do not change the driver's role in any meaningful way.
    - *Level 1: Driver Assistance* — Either lateral or longitudinal control of the vehicle is automated under some conditions (within a specified operational design domain or ODD), while the driver performs the other control functions and continuously monitors the driving environment for hazards. (Example: adaptive cruise control.[4])
    - *Level 2: Partial Automation* — Both lateral and longitudinal control of the vehicle is automated within a specified ODD, while the driver continuously monitors the driving environment for hazards. (Examples: current highway driving systems offered by Tesla,[5] Mercedes[6], Volvo[7], and others.)
    - *Level 3: Conditional Automation* — Both lateral and longitudinal control of the vehicle is automated within a specified ODD without continuous driver monitoring but depends on the driver to provide a "fallback" intervention on short notice to maintain safety when the system requests help in managing a hazardous situation that it cannot handle itself. (Example: Audi in non-U.S. market).[8])
    - *Level 4: High Automation (Select Driving Tasks)* — The complete dynamic driving task is automated within a specified ODD, with enough fallback capability engineered into the system that it can guarantee transitioning the vehicle to a minimal risk condition regardless of the hazard encountered. (Examples: automated people movers on segregated guideways[9], prototype driverless low-speed shuttle vehicles[10], heavy trucks in fenced-off mines[11], and many vehicles that developers are attempting to develop that will provide driverless taxi-like services within highly constrained ODDs.)
    - *Level 5: High Automation (All Tasks)* — Similar to Level 4 systems, but Level 5 CAV systems are able to perform all dynamic driving tasks in the full range of roadway, traffic, weather and environmental conditions in which humans are able to drive.

      Note: The definitions of automation levels provided above focus on the role of the driver, but the developers of more highly automated systems are also defining roles for remote supervisors or dispatchers who could intervene to assist some Level 4 vehicles without drivers when they get in trouble.

- *Operational design domain (ODD)* — An ODD is the specific conditions under which a given driving automation system is designed to function, including driving modes. An ODD may include geographic, roadway, environmental, traffic, speed and/or temporal limitations. The driving modes could include fully access-controlled highways in either low-speed or high-speed driving conditions, or low-speed urban driving in sites that are protected from intrusions by most other vehicles. It is essential for the designer of the system (and the assessor of its impacts) to precisely specify the ODD. Representative examples of the attributes are provided below, but there is no expectation that these would be modeled explicitly. Rather, they can be used to support estimates of the percentage of all driving that could be done by any specific driving automation system to be studied. ODD attributes to be considered for an automation system include:
    - Roadway type (expressway/freeway,[ii] rural highway, suburban arterials, urban streets, suburban residential streets, pedestrian zones, bicycle paths, segregated paths, etc.)
    - Traffic conditions/speed range (freeway at free flow, congested freeway, high-speed arterial, medium speed arterial, low-speed city streets, low-speed residential streets, walking/running speed with pedestrians, low-speed parking lots, etc.)
    - Geographical boundaries (city neighborhood, college campus, office park, retirement community, resort community, public park, etc.)
    - Weather and lighting constraints (rain, snow, fog, dust, wind, low sun angles, nighttime darkness, etc.)
    - Roadway anomalies (work zones, emergency responders, erratic drivers, animals, road debris, etc.)
    - Supporting infrastructure (pavement markings, signage, street lighting, physical segregation by curbs or barriers, cooperative traffic signal control, etc.)

1.1.2.1 Confusion in Concepts Related to Connected and Automated Vehicles versus "Autonomous" Vehicles

SAE J3016 includes detailed explanations about why terms such as "driverless," "self-driving," and "autonomous" should generally be avoided, because of the confusion that they create when they are applied indiscriminately to wide ranges of driving automation systems. Most of these systems are indeed NOT "driverless," but they change the role of the driver. There is one limited class of vehicle, referred to as "automated driving system (ADS)-dedicated vehicles," that is designed to operate without any in-vehicle driver controls, and those are the only ones that should be considered "driverless." Problems with "autonomous" and "autonomy" are even more severe and widespread because these terms have been used as synonyms for "automated" and "automation" respectively, but their meanings are in fact very different. "Autonomy" refers to independence and self-sufficiency rather than replacing humans, and "autonomous" is a modifier that should be applied only to the limited subset of automation systems that are designed to operate self-sufficiently, without benefit of V2V or V2I communication or cooperation. "Automation" refers to the substitution of electronic and/or mechanical systems for human labor, which is indeed the central concept most of the time. With this distinction in mind, many of the technologies discussed in this report should be considered connected and automated vehicles (CAVs) since they typically rely on both automated controls of some degree as well as information provided via connectivity.

[ii] High-speed controlled access highways are called by different names in different parts of the U.S. This report will use "freeway" to refer to them.

1.1.3 CAV Emerging Business Models and Utilization Scenarios

Descriptors of vehicle operations are largely decoupled from the previous descriptors of connectivity and automation; thus different levels of connectivity and automation can be applied to vehicles characterized by the business/utilization scenarios discussed below with relatively limited consideration of coupling effects.

- *Private use* — Conventional, privately owned and operated vehicles.
- *Car-share* — In this vehicle business model, drivers are able to use a pool of vehicles a short distance from their home or office for limited-duration trips. Unlike traditional car rental companies that charge by the day and typically require substantial transaction time, this approach is designed for rapid, seamless access with use times as small as a few minutes. One-way car-sharing adds flexibility by freeing drivers from having to return cars to the same location; a variant on this idea is free-floating car-sharing, in which vehicles can be left in any legal parking space anywhere within a defined region.
- *Ride-sourcing* — Unlike car-sharing, ride-sourcing or ride-hailing provides "drivers" and can offer door-to-door service. Recent innovation has allowed anyone with a smartphone app to hail a ride and anyone with a vehicle to become a driver; the ride-matching process has become an automated process facilitated by advances in routing technology. Pooled ride-hailing trips are also becoming a popular way to save consumers money while enhancing vehicle utilization, and are possible because of sophisticated routing algorithms. Companies providing these services are now referred to as transportation network companies (TNCs).
- *Public transit-like* — Traditional public transit operates fleets of dedicated large-capacity vehicles, sometimes in dedicated corridors (e.g., bus lanes, rails) according to a predefined schedule. Combining this type of service with TNC approaches and low-speed automated shuttles could allow for synchronization of first- and last-mile transport within transit corridors, either with the same or different vehicles, and provide service to routes not typically served by public transit. Schedule flexibility may also become possible if the transit service can coordinate the itineraries of all riders, so that vehicles leave right after customers arrive, rather than at predefined times.
- *Private goods delivery* — On-demand transport of goods looks much like the transport of people using ride-hailing. These are to be distinguished from technology designed to operate exclusively on sidewalks, which falls outside of the scope of current research discussed in this report. In addition to traditional take-out food delivery services, TNCs are now embracing this business model and are also expanding delivery to other items, such as groceries. Brick-and-mortar stores as well as online retailers now offer delivery of any item in stock within a few hours, and many companies are exploring non-traditional vehicles (e.g., aerial drones) to enhance efficiency.[12]
- *Common carrier goods delivery* — Traditional and express mail delivery (U.S. Postal Service, UPS, FedEx, etc.) is now being complemented by new entrants offering faster, more flexible services, perhaps most visibly led by Amazon. The line between private and common carrier goods delivery is blurring, with more companies offering rapid delivery services as commerce moves online.

1.1.4 External Influences (Infrastructure and Transportation Policies)

CAV systems do not often operate in isolation; rather, they rely on roadway infrastructure as their runway, and their usage is governed by transportation policies created at the local, state, or federal level. These external factors can have significant influence on how CAV systems operate and on their contributions toward transportation energy consumption (or savings).

- Roadway infrastructure changes that could influence CAV usage include:
    - Construction of new roadway infrastructure in established corridors or as a way of stimulating development in new corridors, with a specific intent to support CAV features or operational constraints

  - Segregation of roadway infrastructure for connected vs. unconnected or automated vs. manually driven or freight vs. passenger vehicles, simplifying the operating environment for CAV systems
  - Widespread implementation of I2V and V2I communication systems throughout the roadway infrastructure, supporting CAV applications
  - Upgrades to roadway infrastructure signage, markings and geometry to make roads friendlier for automated vehicle operations and to enable higher levels of automation to be deployed earlier
- Transportation policy changes that could interact with CAV system usage include:
  - Roadway usage pricing based on measures other than fuel consumption, such as mileage-based fees or peak-period congestion charges
  - Changes in the gasoline tax at federal and/or state levels
  - Pricing or traffic priority policies to encourage shared vehicle occupancy
  - Restrictions on availability of parking or pricing mechanisms that influence parking location
  - Insurance pricing regulations that consider technologies such as collision warning and avoidance or automated driving systems
  - Federal Motor Vehicle Safety Standards (FMVSS) or other regulations specific to higher levels of automation in new vehicles
  - Incorporation of CAV features into fuel economy standards

1.2 Overview of Preliminary CAV Bounding Study Analysis and Identified Research Gaps

Before creating the DOE SMART research consortium, DOE performed a study to address the ranges (bounds) of potential effects of connected and automated vehicle (CAV) technologies on vehicle miles traveled (VMT) and vehicle fuel efficiency.[13] The report from this study (generally referred to as the “Bounding Study”) was instrumental in setting the foundation for subsequent SMART consortium efforts, as well as identifying research gaps to be assessed in greater detail by the consortium, and thus provides a starting point for the consortium’s research goals and objectives.

The Bounding Study, based on a review and synthesis of existing CAV literature, made it clear that there is enormous uncertainty about the potential long-term impacts if fully automated and highly connected vehicles replace nearly all light-duty passenger vehicles in the United States (the Bounding Study used 100% penetration of new technologies for each assessment case). Scenarios representing lower and upper bounds of changes in fuel use for a national fleet of conventional powertrain vehicles were assessed, with projected energy use reductions of as much as 60% of current U.S. light-duty vehicle (LDV) fuel consumption to an increase as high as two times (200%) the current level of U.S. LDV fuel consumption. The wide range between the lower and upper bounds of future vehicle energy use reflects the large uncertainties about ways that CAVs can potentially influence vehicle efficiency and use through changes in vehicle design, purpose of use, driving, travel behavior, management and policies. In addition, significant uncertainty exists about future CAV technology adoption rates. Use of alternative powertrain technologies such as vehicle electrification will be expected to reduce both the upper and lower bounds of fuel consumption for the scenarios examined in the Bounding Study. However, the relative impact of different CAV features on advanced powertrains is expected to be different from the corresponding impact on conventional vehicles, so future work should more rigorously explore the combined impacts of advanced powertrain and CAV technologies.

1.2.1 Bounding Study — CAV Impact Factors Affecting Light-Duty National-Level Fuel Consumption

Generally, the factors impacting national-level fuel consumption as identified in the bounding report can be grouped into three categories: those that influence: (1) vehicle fuel consumption per mile, (2) travel demand or VMT, and (3) CAV adoption. Of the fuel efficiency impacts considered in the bounding study, vehicle/powertrain resizing offered the largest potential decrease in energy consumption per mile, albeit based on assumptions of radical downsizing. The potential reduction in fuel consumption by changing drive profiles and smoothing traffic flow is also large. Most of the vehicle-centric factors identified and considered in the bounding study can potentially decrease fuel consumption per mile with the exception of higher speed travel.

The potential influence of CAVs on travel demand was found to be quite large, with possible increases due to easier travel being the largest component. Repositioning of empty CAVs could increase VMT, but few estimates of this increase were found in the literature, and these estimates were small (a few percent). Increased ride-pooling could decrease VMT, but adoption of ridesharing is very uncertain.

While current driver assistance technology is being adopted at some level, the future adoption levels of advanced CAV technologies are highly uncertain. Costs for such technologies are currently quite high compared to the cost of a conventional vehicle, but are decreasing rapidly with technology development and are expected to decrease much more if produced at large volumes. However, consumer attitudes and preferences for CAVs are not well understood.

1.2.2 Bounding Study Identified Uncertainties and Research Gaps

As discussed above, the most significant drivers of national-level LD fuel use changes were identified for the three factors examined in the Bounding Study. In addition, important data and knowledge gaps for each of these factors were also assessed and prioritized. Based on each factor's importance to estimating future energy impacts and the tractability of addressing the knowledge gaps, the following were identified as priorities.

1.2.2.1 Travel Demand Impact

Analyzing potential changes in travel demand, vehicle use, mode choice, etc., in large-scale simulations with CAVs, and simulating traveler behaviors in appropriate contexts, such as large metropolitan areas or corridors, is necessary to analyze how travel behavior and vehicle use might change with CAVs in different conditions and with new operating capabilities (i.e., zero occupancy vehicles, ZOVs). Ways to expand the results of these simulations to the national scale will also be needed, since high-fidelity national level simulations will not be computationally feasible.

1.2.2.2 CAV Adoption

The impact of CAVs will clearly depend on how many are on the road. Consumer choice models need to be extended to include choices such as whether to buy a vehicle or use an individual vehicle sharing service or ride-hailing, and whether to buy a vehicle with CAV capabilities as well as other attributes (e.g., powertrain type). Results of projected adoption levels will be needed in travel behavior simulations and energy analyses. More data on consumer preferences for CAV features will be needed.

1.2.2.3 Vehicle Fuel Efficiency Impacts and Redesign

While a number of vehicle-level studies have provided important results on potential influences of CAV technologies on vehicle efficiency, much work remains in analyzing efficiency effects under a wider range of conditions and for more powertrain types. In the long term, because CAVs may be designed much differently from current LDVs with drastic downsizing, less crash protection, different performance characteristics, and other changes, energy consumption needs to be analyzed for a wide range of vehicle configurations. Methods will be needed to map the vehicle-level analysis results to the entire U.S. on-road fleet under relevant conditions.

1.2.2.4 Heavy-Duty CAVs

For a range of CAV capabilities, potential adoption levels and impacts on operation and the resulting energy use for heavy-duty vehicles need to be assessed. In particular, the Bounding Study identified that more work is needed to estimate the fraction of VMT that could be driven by long-haul freight trucks in platoons and the potential energy savings of the vehicles operating within the platoon — something that both the SMART Mobility Consortium Multi-Modal/Freight Pillar as well as the SMART Mobility Consortium CAVs Pillar subsequently investigated in their respective research plans.

1.3 CAV Pillar Research Focus Areas

Through control and optimization, CAV technologies offer the potential for improving vehicle efficiency and possibly reducing overall transportation energy usage from the vehicle level to the corridor level and the regional level. Furthermore, connectivity and automation may also promote further vehicle electrification due to more convenient, transparent and informed BEV charging and usage. However, increased vehicle and transportation efficiency are at risk of being negated by an increase in vehicle miles traveled (VMT) due to due to possible rebound effects (driving more because connectivity and/or automation makes it easier and/or cheaper) as well as new vehicle usage cases. Therefore, a systems-centric research effort is necessary to better identify energy saving opportunities while identifying strategies to discourage detrimental operations to the largest degree possible.

This work seeks to study CAV technologies using reliable models, analytical methods and experimentation to predict the greenhouse gas (GHG)/energy/cost implications of CAVs and their associated infrastructure components across a range of technology development, market penetration and traveler behavior scenarios. More specifically, this work seeks to address three primary research questions:

1) How will connected and automated vehicles and systems behave in the real world?
2) What are the GHG, energy, technology and usage implications of connectivity, automation, and the combination of both technologies?
3) What is the best way to harness CAVs for reduced energy use and improved mobility in transportation?

1.4 Overview of Capstone Report Layout and Findings

The remainder of this work seeks to describe the approaches, findings, and relevance of the research efforts associated with the CAVs Pillar of DOE’s SMART Mobility research consortium:

- Section 2 National-Level Connected and Automated Vehicle Impact Synthesis provides an overview of a national-level CAV outcomes and scenario synthesis report to reassess and expand the preliminary analysis of the Bounding Study regarding the impacts of CAVs, utilizing the SMART consortium’s and others’ recent research findings related to connected and automated vehicles.
- Section 3 Research Findings discusses the focus areas and research results of these efforts. The four primary research thrusts for this work are: 1) data-driven experimentation and validation of CAVs concepts (Section 3.1), 2) adapting simulation methods and models to more accurately and robustly incorporate CAV technologies and behaviors (Section 3.2), 3) corridor-to-regional-to-national level impacts and sensitivities of connectivity and automation (Section 3.3), and 4) harnessing enhanced connectivity and automation enabled controls for improved energy outcomes and coordination (Section 3.4).

  While thrusts 3 and 4 are closely related, research thrust 3 specifically focuses on understanding what happens when CAV technologies are introduced at a range of scales (e.g., vehicle, corridor, region), while thrust 4 focuses on enhanced controls and methodologies to leverage the new information and controllability provided by CAV technologies to improve efficiency and congestion.

- Section 5 Summary and Conclusions synthesizes the research findings from the earlier sections and provides high-level answers to the research questions proposed above. Research and data gaps identified though the research performed in this works are also identified and prioritized.

2 National-Level Connected and Automated Vehicle Impact Synthesis Study

As discussed in the Introduction (Section 1.2), a high-level national-scale analysis of the potential impacts of CAVs, the Bounding Study, was published in 2016.[14] That analysis found that energy consumed by light-duty vehicles may decrease by 60% or increase by 200% if there is 100% penetration of CAV technologies. The report also identified key questions for future research. In 2019, the original Bounding Study was revisited using an improved methodology and updated research from the past three years, from throughout the SMART Mobility Consortium and from other researchers. Key findings from the updated CAVs study, the Synthesis Study, are the following:

- On average, energy use increases by approximately 10%, but with a wide distribution of possible cases.
- 60% of cases lead to an increase in energy consumption, and 90% of cases are between -40% and +70% energy change.
- 90% of scenarios show an increase in VMT, with a mean increase of 40%, while the mean improvement in fuel economy is a 20% reduction in fuel consumption.
- The top factors leading to an increase in energy usage are additional travel as it becomes easier and cheaper, repositioning of empty vehicles, and on-vehicle electronics power draw, while the largest potential levers for reducing fuel consumption are vehicle rightsizing, ride-pooling, and drive smoothing.

Like its predecessor, the CAVs Synthesis Study continues to highlight factors that change travel demand or change vehicle operational efficiency, but it provides a more complex analysis than a simple bound on the change in energy consumption. On the travel demand side, the factors are grouped into three major classes of changes in LDV travel patterns: (1) changes in personal mobility, where people make trips that they would not have made in the absence of CAVs, (2) changes in on-road travel, where VMT may change but individuals' origins and destinations remain the same, and (3) changes in commercial-based household travel activity, for trips that are directly impacted by the advent of CAV technologies. These factors were explored to ultimately answer one question: Will connected and automated cars be driven more (or less) than today's vehicles? For changes in vehicle efficiency, three major classes of changes due to CAVs are: (1) how the vehicle operates, (2) how the vehicle is electronically connected to external nodes, and (3) how a connected and automated vehicle is designed. The factors described here address a second question: Will connected and automated cars be more (or less) efficient than today's vehicles?

The factors in each class are described in more detail below. Each factor is informed by the latest available research from the SMART Mobility Consortium and elsewhere and is quantified as the percentage change compared with a world without automated vehicles. This includes direct changes (for example, improvements to fuel economy from more steady acceleration) and induced changes (such as changes in traveler behavior, including changes in commuting patterns and ride-pooling, because CAVs are cheaper to operate than human-driven vehicles). In the CAVs Synthesis Study, both direct and induced changes are attributed to connectivity and automation, as they are enabled by CAV technologies. Figure 2-1 shows the twenty-four factors that the CAVs Synthesis Study considered when calculating the impact of CAV technologies on national-scale VMT and energy consumption. The text that follows describes each factor and how it may change with CAV adoption. Note that these narratives are representative of specific scenarios, and individual factors may actually change in the opposite direction of the most commonly presented narrative.

	Travel Demand			Energy Efficiency			
Personal mobility	1	Shifting travel patterns - sprawl		13	Vehicle congestion		Vehicle operation
Personal mobility	2	Shifting travel patterns - urbanization	New	14	Faster travel		Vehicle operation
Personal mobility	3	Additional travel - underserved		15	Drive smoothing		Vehicle operation
Personal mobility	4	Additional travel - leisure travel	New	16	Platooning		Connectivity
On-road travel	5	Mode shift to/from roads		17	Intersection management		Connectivity
On-road travel	6	Eco-routing	New	18	Off-board computation & data centers	New	Connectivity
On-road travel	7	Ridepooling		19	Electronics power draw	New	Vehicle design
On-road travel	8	Empty VMT (deadhead)		20	Aerodynamic drag	New	Vehicle design
On-road travel	9	Fueling trips	New	21	Engine downsizing	New	Vehicle design
Commerce	10	Efficient parking		22	Vehicle rightsizing		Vehicle design
Commerce	11	Home delivery	New	23	Vehicle lightweighting	New	Vehicle design
Commerce	12	Sponsored travel	New	24	Vehicle upsizing	New	Vehicle design

Figure 2-1. Factors leading to demand and efficiency changes for light-duty CAVs, including notation of which factors were not included in the 2016 CAVs Bounding Study.

Changes in personal mobility:

- *Shifting travel patterns due to sprawl* is frequently cited as one of the major levers for changes in VMT due to connected and automated vehicles, as automated vehicles may make traveling much easier. If the burden of travel is reduced, perhaps people will live further away from their jobs and urban areas, leading to increases in VMT.
- At the same time, automated vehicles may minimize sprawl by making urban travel less burdensome and more attractive. *Shifting travel patterns due to increased urbanization* may arise due to easier driving and parking of CAVs, along with opportunities for transportation as a service to replace personally owned vehicles.
- *Currently underserved populations* (e.g., the elderly, disabled, poor, young) may greatly increase their travel if automated vehicle travel is cheaper or easier than today's available transportation options.
- *Leisure travel* for shopping, entertainment, and dining may increase due to minimized travel costs and the reduced burden of travel.

Changes in on-road travel:

- *Mode shift* to and from alternative modes of transportation (e.g., public transit, biking, airplanes) was found to be a relatively small component, but will still be included in this study.
- For connected vehicles, knowledge of traffic conditions could lead to *eco-routing* to minimize fuel use by avoiding congested areas. Eco-routing involves taking an alternate route to minimize fuel consumption, though potentially at the expense of additional VMT. Rerouting could potentially increase fuel consumption if the traveler views time as more important than fuel use.
- *Ride-pooling* is defined as multiple passengers from nearby locations traveling the same route in the same vehicle for the majority of their travel. The size of changes in VMT from ride-pooling will be notably different depending on ownership paradigms.
- *Empty miles traveled* will occur when a vehicle is traveling from the passenger's final destination to the next location for the vehicle, be it a personal garage, a parking space, or, for shared vehicles, to pick up the next passenger.
- Changes in when and how fueling trips are made for self-driving vehicles could occur if passengers expect vehicles to refuel or recharge when they are not in the vehicle. Since a majority of refueling

trips today are pass-by trips, this *change in fueling trips* could result in an increase in vehicle miles traveled.

Changes in commercially linked household travel:

- The energy use and emissions from vehicles *searching for parking* can be high in urban centers. CAVs may have foreknowledge of the availability of parking, or eliminate the need for parking in congested areas altogether.
- CAV technologies may cause *reduced or increased shopping trips*. Shopping trips make up nearly 15% of household travel, according to the most recent National Household Travel Survey.[15] In a highly automated world, automated package delivery may be cost effective and convenient, reducing household vehicle travel while perhaps increasing delivery trips by other vehicles outside of the light-duty vehicle segment.
- In *sponsored travel*, a company will pay for some portion of a trip, either to present advertising to the rider or to bring customers to a specific shopping or tourist destination. This reduction in cost may add passenger travel.

Changes in operational vehicle fuel consumption:

- *Reduced congestion* because of fewer accidents and improved vehicle operation will help traffic flow and may impact energy consumption, but may also lead to increased travel.
- Improved vehicle safety is potentially one of the large benefits of vehicle automation. With reduced risk of accidents, vehicles can potentially *travel faster* than typical highway speeds of today.
- *Drive smoothing* due to automated vehicles can save energy. This factor includes both conventional and cooperative adaptive cruise control systems. Automated vehicles will be able to drive more smoothly than human drivers, yielding more efficient acceleration and deceleration profiles, though interaction with other vehicles may reduce or negate vehicle- and system-level benefits. Additionally, with knowledge of upcoming energy needs beyond instantaneous power loads, engines can be optimized to operate in their most efficient modes, as is being studied in ARPA-E's NEXTCAR projects[16], which aim to reduce energy consumption by 20% or more.

Changes in energy consumption caused through connectivity:

- *Platooning* of close-following vehicles can reduce aerodynamic drag and minimize fuel consumption.
- *Intersection management* is related to drive smoothing but focuses solely on improving the efficiency of the acceleration and deceleration inherent to signalized intersections and highway on-ramps.
- *Energy consumption for telecommunications and data processing* can potentially be large. This energy is supplied by electricity, rather than motor fuel, but does scale with vehicle demand, and is treated similarly in this analysis.

Changes in vehicle design:

- The *power draw of automated vehicle machinery and electronics* will add an accessory load that hinders fuel economy. The accessory load from running dedicated computers and sensors for automated driving can potentially increase energy consumption by a third.
- Test vehicles currently have large sensor equipment which increases the *aerodynamic drag* of CAVs. Similarly, CAVs may be able to be designed in a way to minimize drag forces, for example, by removing side-view mirrors.
- CAVs have the opportunity for *engine downsizing*. CAVs will have less need for high rates of acceleration, so vehicle performance can be de-emphasized in favor of fuel economy.
- *Vehicle resizing* was previously identified as having a significant impact on total energy consumption. One common narrative is that since most travel is solo travel, very small cars can be used instead of larger cars to improve fuel economy.

- For fully driverless CAVs, features such as steering wheels can be removed from the car, yielding fuel economy improvements from *vehicle lightweighting*. If CAVs are considered safe enough, and there is 100% penetration of CAVs, safety features such as airbags and reinforced frames can possibly be removed from vehicles as well.
- This analysis also explored the possibility of *larger vehicles* with increased seating capacity or a more feature-rich interior.

In the CAVs Synthesis Study, it is assumed that the technology has 100% market penetration. The change in total VMT is calculated by taking the multiplicative product of the changes due to each of the 12 travel demand factors, and the change in average vehicle fuel consumption is the product of the changes due to the 12 energy efficiency factors. The total change in energy due to light-duty CAVs is the product of all 24 factors. The values for each of these factors were derived from a thorough literature review, exploring over 500 peer-reviewed journal articles, technical reports, white papers, press releases, and other literature. Rather than using a single value to describe each factor, as in the 2016 CAVs Bounding Study, the CAVs Synthesis Study compiles results from multiple relevant studies to generate triangular distributions for each factor and uses Monte Carlo simulations to quantify changes in total energy consumption and VMT. The upper and lower bounds of each distribution are simply the largest and smallest values from the literature for each of the factors. The peak of the triangular distribution for each factor is generated by a weighted average of the total change in energy consumption or VMT due to that factor, as identified in the literature, giving more weight to more rigorous and analytical research and less weight to studies where assumptions and methodology were unclear. Using a triangular distribution includes all scenarios relevant to estimating changes due to CAVs, while not giving undue weight to extreme values as would happen with a uniform distribution.

The six-step calculation methodology is summarized in Figure 2-2, where each step of the quantification is color-coded. In this figure, the red triangles represent sample triangular distributions, green dots represent single values selected at random from each triangular distribution for each factor, purple arrows show adjustments made due to interactions across factors, and the orange dot shows total changes across all factors for a single Monte Carlo simulation. Thousands of simulations are aggregated, resulting in the histograms for energy and VMT shown in blue.

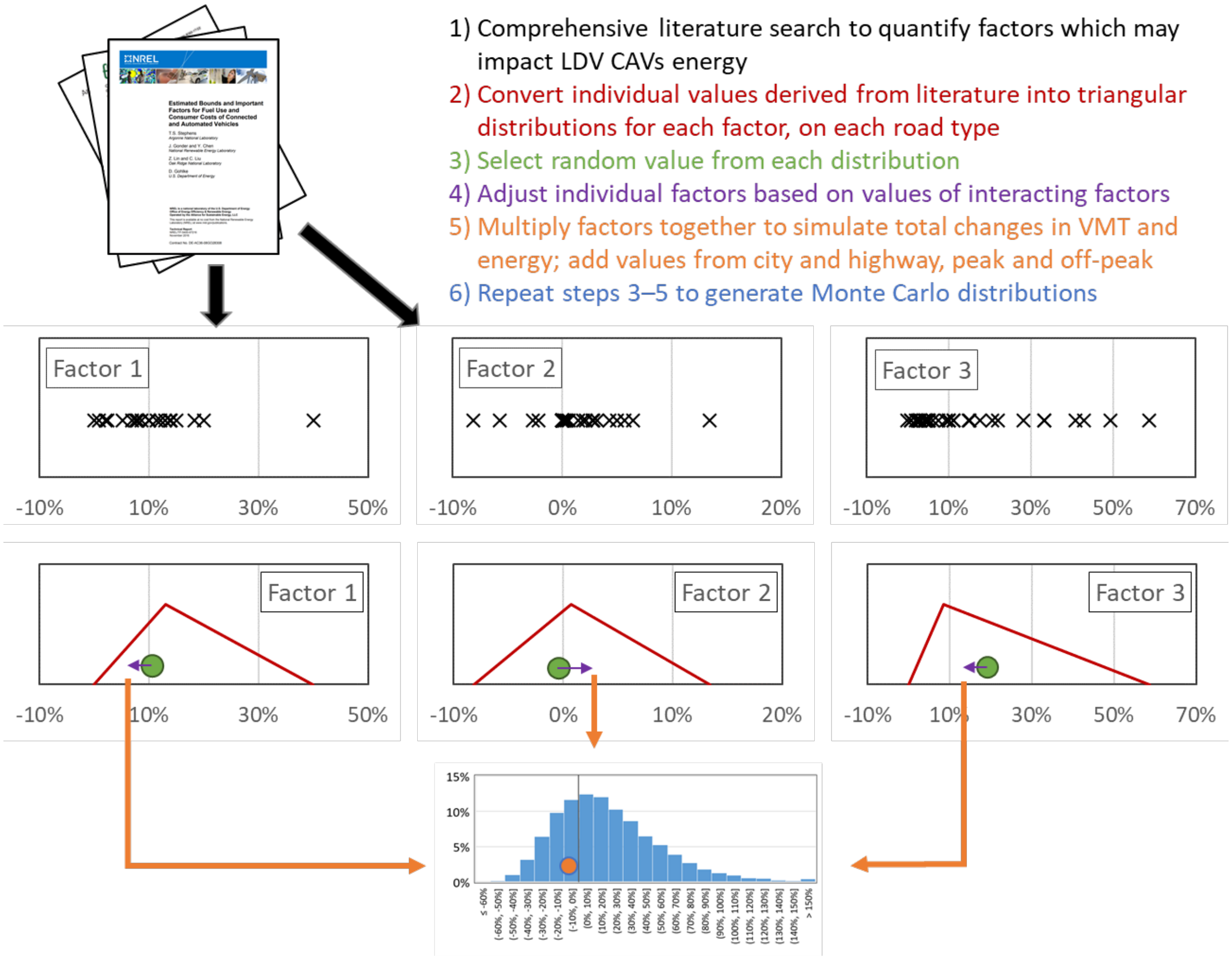


Figure 2-2. Analytical framework for CAVs Synthesis Study.

Within each iteration of the Monte Carlo simulation, values are randomly selected for each factor from its respective triangular distribution. Using a multiplicative product of the different factors to calculate total changes in VMT and energy consumption is, strictly speaking, only correct if each factor is independent from each other factor. Since these factors are intertwined, each factor is adjusted based upon the values of the other factors to account for interdependencies. For example, it is perhaps infeasible for a vehicle to be drastically downsized if it is going to be used for ride-pooling. Therefore, if a simulation calls for a high degree of pooled rides, the value for vehicle resizing will be adjusted. Similarly, if a simulation assumes major vehicle downsizing, then ride-pooling will be minimized.

Vehicles have different travel behaviors and different fuel economies on different road types, and each of these factors may have different impacts on different road types. For instance, platooning and high-speed travel are relevant factors for free-flow highway driving, while efficient parking is relevant for low-speed, congested city driving. Therefore each Monte Carlo simulation treats these road types separately, partitioning travel into city travel and highway travel, and further partitioning these trips into peak (i.e., congested) and non-peak (i.e., free-flow) travel, as was done in the original CAVs Bounding Study. In this analysis, each factor has a triangular distribution for each of the four road types. Fifty-seven percent of baseline travel is assumed to be city travel, matching the mix used by the U.S. Environmental Protection Agency (EPA) for calculating vehicle fuel economy, and 35% of all travel is assumed to be at peak travel times, using results from Chen et al. [17] Finally, VMT and energy consumption across road types are aggregated to find national-scale impacts of CAV technologies.

Figure 2-3 shows the ranges from the literature of the total changes in travel demand and vehicle fuel efficiency for each of the 24 factors, across all road types. The lowest and highest values from the literature are the bottom and top of each bar, respectively. Within the bar there are two markers. The horizontal line represents the peak of the triangular distribution, determined through weighting each value found in the literature. The small X on each bar represents the mean value when pulling a number from this distribution.

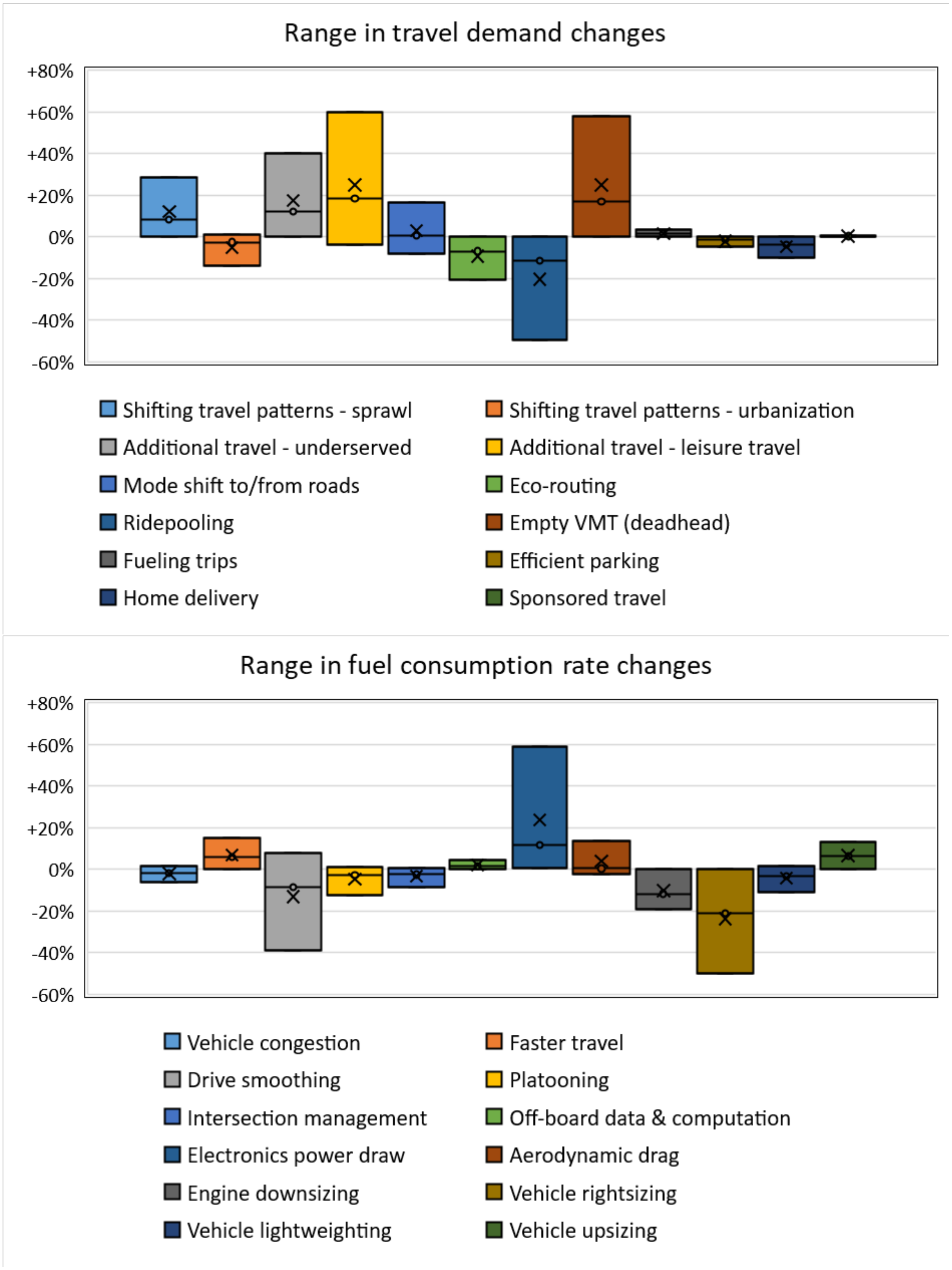


Figure 2-3. Literature results of potential changes in different factors impacting CAV travel demand and fuel consumption rates.

Figure 2-3 shows that the top factors leading to an increase in energy usage are induced travel due to easier and cheaper travel (both additional travel by today's travelers and new travel by the currently underserved), repositioning of empty vehicles, and on-vehicle electronics power draw, while the largest potential levers for reducing fuel consumption are vehicle rightsizing, pooled ride-hailing, and drive smoothing. No single factor is estimated to change energy consumption by more than a factor of two, though 9 of 24 factors are estimated to change total energy consumption by more than 10%. Factors such as ride-pooling have large variations due to considering different scenarios with widely different futures, with most of the highest potential for VMT reductions coming from scenarios with centrally owned vehicle fleets. Other factors have a large range of potential outcomes within the same scenarios, such as electronics power draw, with considerable uncertainty in the size of typical auxiliary electrical loads for CAV hardware.

Figure 2-4 shows histograms representing the distributions for changes in VMT, changes in fuel consumption rate, and changes in total energy consumption for 100,000 simulations. (Note that the total energy distribution is not simply the product of the travel demand and fuel consumption distributions, as these factors are adjusted within each simulation.) The average change for these metrics across all 100,000 simulations is a 40% increase in VMT, a 10% decrease in the fuel consumption rate, and a 10% increase in total energy consumption, though these distributions have very long tails. While in general travel increases and fuel consumption decreases, in 10% of the scenarios total travel decreases, and in 10% the fuel consumption rate increases. The minimum and maximum values are far removed from the majority of all simulations, as can be seen in the figures above.

Results from this project show that while the overall bounds describing the maximum and minimum energy consumption are driven by outliers for each factor, allowing for uncertainty in the calculations will lead to much more modest impacts. The previous CAVs Bounding Study noted the potential for fuel economy to increase fuel consumption by 200% or decrease it by 60%. This highlighted the potential uncertainty in energy consumption when many factors work in concert with each other. However, this range was driven by unlikely outlier points and not representative of any plausible scenario. Reproducing this methodology using the expanded the set of explored factors and new literature from the last three years yields expanded bounds of -96% to +1500%. It should be noted that these values are the extremes, which by definition have an infinitesimal probability. As can be seen in the distributions shown in Figure 2-4, these bounds are well outside the ranges where combinations of factors are remotely probable, hence it is inappropriate to use these bounds to estimate VMT, fuel economy, or total energy consumption.

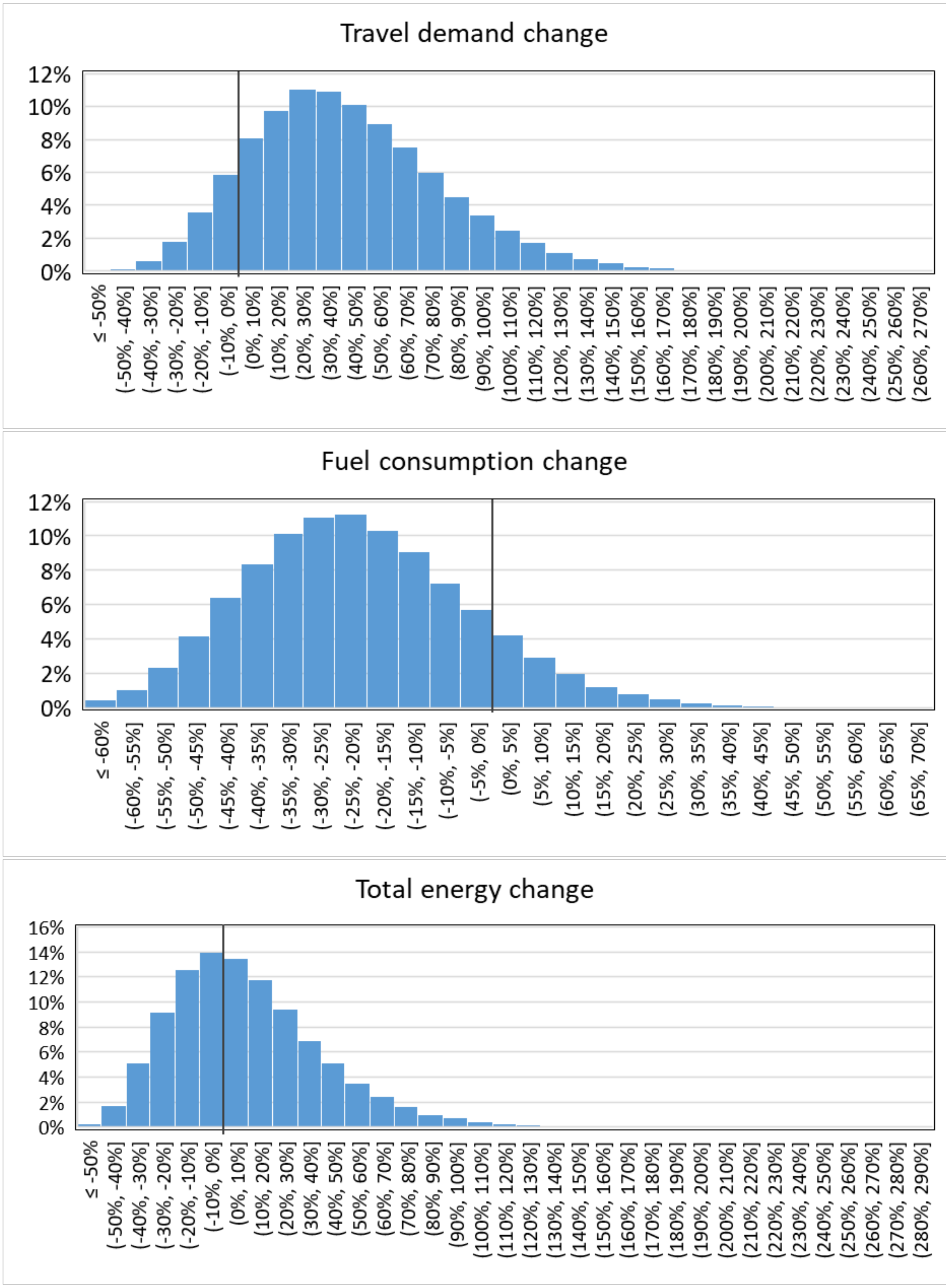


Figure 2-4. Histograms for potential changes in VMT, fuel consumption rate, and energy consumption due to CAV technologies.

The broad distributions in Figure 2-4 arise from many different possible futures. The CAVs Synthesis Study explored specific scenarios to determine factors that drive changes in energy consumption and VMT. For example, the CAVs Synthesis Study examined two scenarios related to vehicle ownership. One of the prevailing themes discussed in white papers describing new mobility is the possibility of wholesale changes in vehicle ownership.[18] The general idea is that if there are no drivers to be paid, fleet-owned vehicles used for ride-hailing can become incredibly inexpensive on a per-mile basis compared to the status quo. The first of the ownership scenarios generates triangular distributions for each factor based on a down-selection of the literature, using results for a fleet of vehicles that are essentially entirely privately owned, as in today's ownership paradigm. The second ownership scenario is one in which vehicles are almost entirely fleet-owned, and operations are entirely fleet-managed. Figure 2-5 and Figure 2-6 show distributions for VMT, fuel efficiency, and fleet-wide energy consumption for these two scenarios.

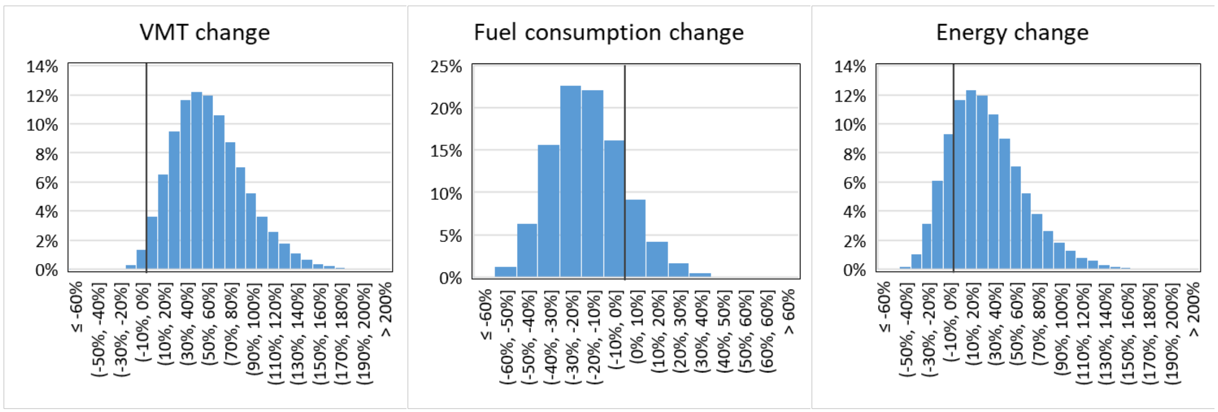


Figure 2-5. Histograms for potential changes in VMT, fuel consumption rate, and energy consumption due to CAV technologies; privately owned vehicle scenario.

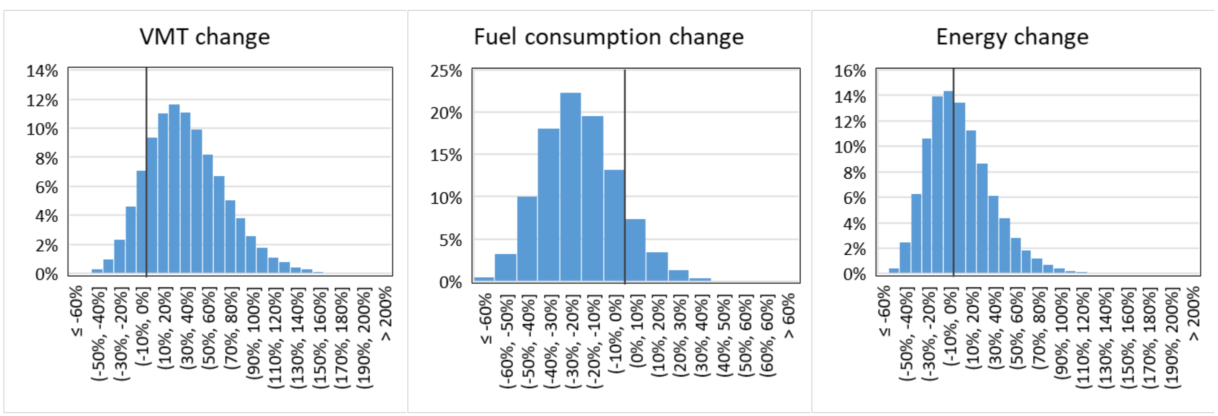


Figure 2-6. Histograms for potential changes in VMT, fuel consumption rate, and energy consumption due to CAV technologies; fleet-owned vehicle scenario.

These figures show that the total energy consumption is higher in the privately owned scenarios, due to relative increases in both travel demand and fuel consumption rates. Total fuel consumption increases by 5% in the fleet-owned scenario and by 30% in the privately owned scenario. The average VMT increases by 40% in the fleet-owned scenario and by nearly 60% in the privately owned scenario. The privately owned scenario has a higher overall VMT than the fleet-owned scenario due to a much lower incidence of ride-pooling. Vehicle efficiency is improved in the fleet-owned scenario because vehicle rightsizing is more prominent in that scenario. Most of the other individual factors have similar results in both of the scenarios. Notably, empty VMT is similar in the two scenarios, though with different interpretations: In the privately owned scenario, this describes vehicles returning to their homes to wait for their owners, while in the fleet-owned scenario, deadheading represents vehicles traveling to their next rider.

In summary, the CAVs Synthesis Study builds upon the previous CAVs Bounding Study by incorporating a larger pool of research, especially results found through the SMART Mobility Consortium, and by improving methodology to allow for distributions of each factor and more thorough scenario analysis. On average, this analysis finds that light-duty energy consumption increases by approximately 10% due to CAV technologies, and 90% of simulations are within the range of -40% to +70%. The top factors leading to increases in energy usage are induced travel from easier and cheaper travel, repositioning of empty vehicles, and on-vehicle electronics power draw, while the largest potential levers for reducing fuel consumption are vehicle rightsizing, ride-pooling, and drive smoothing.

3 Research Findings

Building upon the research questions and focus areas described in the introduction, this section provides insights and results from across the various projects and themes investigated in the SMART Consortium CAV Pillar's research efforts.

Section 3.1 discusses the wide-ranging experimental research undertaken to answer the question **"How will connected and automated vehicles and systems behave in the real world?"** Experimental results and insights span both heavy-duty and light-duty vehicles and employ a mix of laboratory, track, in-field, and large-scale fleet data collection and experiments.

Based on the insights and data in Section 3.1 Experimental Research and Analysis, Section 3.2 discusses the CAV-specific modeling adaptations, methodologies, and approaches utilized in these efforts to better model the impacts of CAV technologies and strategies. Building on more than 15 years of modeling and simulation expertise, the methods applied in this section integrate DOE's high-fidelity and validated modeling tools and approaches with state-of-the-art CAV data, capabilities, and controls. Highly integrated tools at various analysis levels (e.g. vehicle-specific, corridor, and regional) are critical for accurately and robustly understanding the impacts of CAV technologies, especially across the entire range of conventional and electrified powertrains in DOE's technology portfolio.

Utilizing the methods and tools developed in the previous section, Section 3.3 discusses a range of case studies that investigate the second research focus of this work: **"What are the GHG, energy, technology and usage implications of connectivity, automation and connectivity?"** More specifically, these efforts investigate the vehicle-level, corridor-level, regional-level, and national-level implications and sensitivities related to introducing CAV technologies into a transportation system. Section 3.3 explores the question "*what if CAVs show up with minimal energy-centric behaviors and controls?*" and builds the foundation and baseline for Section 3.4, which directly leverages the new information and controllability afforded by CAV technologies for improved outcomes related to reduced energy consumption, improved traffic flow, and reduced congestion.

While Section 3.3 seeks to investigate the "what if" questions related to CAV technologies, Section 3.4 investigates the opportunities to harness connectivity and automation for improved energy and productivity outcomes. Specifically, this section discusses the third primarily research focus of this work**: "3) What is the best way to harness CAVs for reduced energy use and improved mobility in transportation?"** This section provides insights and analysis related to how CAV technologies, controls and high-level coordination strategies can improve traffic flow, decrease overall energy consumption, and facilitate more efficient transportation systems though the application of connectivity and automation specific strategies.

3.1 CAV-Focused Experimental Research and Analysis

This section seeks to address the first research question posed in the introduction: **"How will connected and automated vehicles and systems behave in the real world?"** By assessing a range of commercially available vehicles and systems as well as developing and utilizing CAVs research platforms, insights related to the real-world behaviors, benefits, and challenges associated with CAVs technologies were investigated experimentally within this work. The results and data described in this section are also critical for improved and more realistic CAV simulations. Specifically, the modeling and analytical techniques used to predict the vehicle-level, local, regional and national impacts of CAV systems depend heavily on the application of real-world experimental data for validation. The results of these tests can then be used for updating simulation models and validating analytical assumptions, overcoming one of the most significant limitations – lack of data – to prior attempts to model the impacts of CAV systems. Additionally, as CAVs become more widely available, expanded on-road data collection (including comparable baseline vehicles) will provide valuable direct measurements of their real-world impacts. The following sections highlight findings from such experimentally driven research projects.

Key experimental insights and results include:

- A comprehensive set of experimental Class-8 truck CACC and platooning testing was performed across a range of gap spacing and platoon formations. At the closest separation distance evaluated, 4 m, the average fuel savings for a three-truck platoon with at 105 km/h was about 13%, while two-truck platoons in the same scenario saved 7% on average.
- Other maneuvers, applied transiently during platoon/CACC operation showed a 2%–3% and 1%–2% reduction in the realizable benefits for traffic cut-ins and speed variations respectively.
- The Class-8 truck CACC testing also investigated the thermal and aerodynamic turbulence impacts of the various gaps, providing an experimental analysis of the dynamics and sensitivities of close vehicle following aerodynamics as well as detailed data for thermal and aerodynamics model validation.
- An effort to estimate the national potential for platooning used real-world operational data from 57,000 individual Volvo Class-8 trucks to conclude that 56% of classifiable miles driven were both at speeds where platooning is beneficial and had at least a single partner vehicle, within the same fleet of 57,000 vehicles, available for platoon/CACC formation (and usually multiple partners were available). This degree of availability, combined with the experimentally observed truck platoon fuel savings potential discussed previously, suggests truck platooning could be an effective fuel saving strategy if implemented nationally and coordinated efficiently.
- At the individual vehicle level, analysis of on-road driving data based in Gothenburg Sweden using 18,590 trips from the Volvo Drive Me pilot study, observed that Adaptive Cruise Control led to a 5-7% reduction in fuel consumption, compared to the manually driven vehicles operating within the same study environment.
- While experimental testing of recent conventional, internal combustion engine powered vehicles confirms the generally expected intersection-level benefits for several eco-approach and departure (EAD) strategies, the benefits and sensitivities of EAD strategies diverge significantly for electrified vehicles, with some strategies providing greater impact for electrified vehicles and some strategies showing fewer benefits.
- The data collected during EAD field testing shows a moderate fuel savings of 10% to 20% as compared with adjacent vehicles without EAD operating in an 80m zone centered at a controlled intersection (i.e. 40m before, 40m after). However, within this field testing, the frequency for encountering EAD scenarios is low, making the overall benefits at the trip level very small.
- Field data taken from both signalized and stop-sign controlled intersections show that a significant portion of vehicle stopping occurs when there are no vehicles at the conflicting approach. For the intersections assessed within this study, 80% of stops at signalized intersection and 68% of stops at stop-sign controlled intersections were done with no opposing traffic present. These observations suggest that increased signal control awareness and intersection coordination/information sharing could lead to more efficient operation by enabling fewer stops and smoother traffic flow.
- A large-scale evaluation of green routing opportunities was performed using 45,000 actual trips. For roughly one-third of all trips an alternative, less energy consuming route existed. These alternative routes provided an average fuel consumption savings of roughly 12% compared to the original route. Interestingly, about 50% of these more efficient alternative routes were also observed to provide a shorter travel time in addition to the fuel consumption benefits.
- Field testing of an automated vehicle prototype, provided by an industrial project partner, found automation loads ranging between 300 and 400 W for functionalities including hands-free highway operation (L3) and fully self-driving operation and navigation at lower speeds (L4). These electrical load levels suggest that many automation functions relevant to more efficient operation may be implementable at loads lower than the 2-4 kW experienced by recent driverless-capable pilot fleets.

- In-field data collected from several low-speed automated shuttle pilots suggests that the automated shuttles' low operating speeds significantly increase the relative impact of accessory loads on overall per-mile energy consumption, highlighting the importance of incorporating these loads when assessing the overall mobility impacts of a proposed shuttle implementation. For example, air conditioning loads were found to nearly double the observed per-mile vehicle energy consumption in hot weather, compared to relatively cooler times when the air conditioner was not active.

3.1.1 Heavy-Duty Truck Cooperative Adaptive Cruise Control (CACC) and Platooning Field Research

- Truck platooning begins to show fuel savings due to aerodynamic drag reduction within a trailing gap distance of 87 m, indicating that manually driven trucks following within this distance are already saving fuel. Further evaluations used this trailing gap distance and corresponding fuel savings as the baseline for additional savings.
- Average fuel savings for a three-truck platoon with a 4 m following distance at 105 km/h was about 12.5%, while two trucks in the same scenario saved only 7% on average.
- For three CACC trucks following an SUV, the average fuel saving will be 1.0%~1.5% more than in the scenario of three CACC truck only.
- At following distances longer than 12 m, the third truck (of the three-truck CACC case) saves the most fuel. However, for following distances below 12 m, the middle truck saves increasingly more fuel than the third truck as the distance deceases. This reduction in fuel consumption benefits for the trailing vehicle has been observed at closer following distances. For example, at a 4 m following distance, the middle truck saves up to 17%, while the third truck only saves about 12% over a single truck scenario.
- The effect of traffic cut-ins during CACC operation was found to be only about 2-3% since they were transient behaviors.
- At the overall platoon level, the tested speed variations during CACC operation reduced net measured fuel savings for the three-vehicle system to 5.2% from the 6%–7% expected at a 49 m gap distance and baseline 105 km/h driving speed.
- These results are expected to be transferrable to alternatively powered trucks, such as those with hybrid, hydrogen-electric, or fully electric powertrains, as the fuel savings were caused solely by aerodynamic drag reduction.

This section presents the results of test-track testing intended to exclude the effects of other factors on truck fuel economy and show the fuel savings benefits of reduced aerodynamic drag reduction through reduced distance gaps. Although burning less fuel for the following trucks may mean producing less emissions, the air flow reduction into the engine compartment may affect other emission factors.

In this work the CAV Pillar completed the following research for quantitative test-track evaluation of heavy-duty connected and automated cruise control (CACC) trucks for fuel consumption, following SAE I-1321 procedures, for several scenarios:

- Two and three CACC-equipped trucks following at different time gaps (distance gaps) between 0.14 s and 3.0 s (4 m and 87 m)
- Heavy-duty trucks following LD SUV-type vehicles rather than other heavy-duty trucks
- The impact of cut-ins/outs on overall CACC fuel savings potential
- The effect of speeds varying from 55 mph to 65 mph for the fixed time gap
- The impact of speed variations during system operation on fuel consumption

While V2V-based cooperative heavy-vehicle systems are nearing commercialization, there is a knowledge gap in terms of the performance, reliability, and resiliency of these systems.[19] Of particular interest in the current study is the potential energy savings of such systems. For this research, the CACC concepts and implementation approaches described in several previous works[20,21,22,23,24,25] were applied to a set of three heavy-duty vehicles. Procedures and results from an initial, separate closed-track fuel-economy test of this three-truck CACC system are reported in a previous report[26], with the following discussion focusing on a second round of testing that looked into a larger range of gap distances/times as well as other configurations and issues related to practical platoon implementation.[27] Testing took place at Transport Canada's Motor Vehicle Test Centre (MVTC) in Blainville, Quebec, which is operated by PMG Technologies. The fuel consumption tests were performed on the high-speed test track (BRAVO).[28] The track is a high-banked, parabolic oval with a length of 6.4 km (4 miles). Each day, prior to testing, all vehicles were warmed up for the same amount of time (minimum one hour) at the test speed. The drivers' influence on the results was minimized by conducting the tests on a closed circuit and by strictly controlling the driving cycle and inter-test procedures.

Track testing was undertaken using the SAE J1321 Type II Fuel Economy procedure[29] to investigate the fuel saving potential of the developed truck CACC system. The previous CACC system fuel economy testing examined the effect of vehicle speed (89 and 105 km/h), cargo weight (empty and 15,400 kg/34,000 lb load), and trailer aerodynamics (standard compared to side-skirts and a boat-tail) on the potential fuel savings from platooning.[30] Based on the results from the previous testing, it was decided to use one configuration for the majority of the testing in this study. The following describes the baseline configuration:

- Vehicle speed of 105 km/h (65 mph)
- Total vehicle mass of 29,500 kg (weight of 65,000 lb)
- Same trailer make and model (same make and models as previous testing)
- Trailers outfitted with side-skirts and a boat-tail (same make and models as previous testing)

Compared to the initial set of testing, the three-truck string/platoon was tested at closer distances of 4 m, 6 m, 9 m, and 12 m, representing time gaps at 105 km/h of 0.14 s, 0.21 s, 0.31 s, and 0.41 s, respectively. Separation distances of 17 m, 35 m, and 44 m were re-tested (time gaps of 0.6 s, 1.2 s, and 1.5 s), covering the full range of separation distances previously tested with this CACC system in order to provide a measure of repeatability. Larger separation distances of 58 m and 87 m, corresponding to time gaps of 2.0 s and 3.0 s at 105 km/h, were also tested for these efforts to characterize what vehicles may already be experiencing on the road. To understand potential differences between two-truck and three-truck platoons and to provide a comparative dataset to additional large data sets of two-truck test data[31], four separation distances of 6 m, 12 m, 17 m and 58 m were tested with only two trucks in the CACC string, corresponding to time gaps at 105 km/h of 0.21 s, 0.41 s, 0.6 s, and 2.0 s, respectively.

3.1.1.1 Two- and Three-Truck Platoon Results

- Truck platooning begins showing fuel savings due to aerodynamic drag reduction within a trailing gap distance of 87 m, indicating that manually driven trucks following within this distance are already saving fuel. Further evaluations used this trailing gap distance and corresponding fuel savings as the baseline for additional savings.
- Average fuel savings for a three-truck platoon with a 4 m following distance at 105 km/h was about 12.5%, while two trucks in the same scenario only saved 7% on average.
- At following distances longer than 12 m, the third truck (of the three-truck CACC case) saves the most fuel. However, for following distances below 12 m, the middle truck saves increasingly more fuel than the third truck as the distance deceases. This reduction in fuel consumption benefits for the trailing vehicle has been observed at closer following distances. For example, at a 4 m following distance, the middle truck saves up to 17%, while the third truck only saves about 12% over a single truck scenario.

This testing effort produced the most comprehensive set of platooning energy consumption test results to date. The findings confirm some phenomena observed in previous tests and produce new knowledge. The primary energy consumption trends, as a function of the size of the gaps between the trucks, are shown in Figure 3-1 for each individual truck and for the two-truck and three-truck platoons as a whole. The results compare truck energy consumption when driven in close formation to energy consumption of the same trucks when driven in isolation.

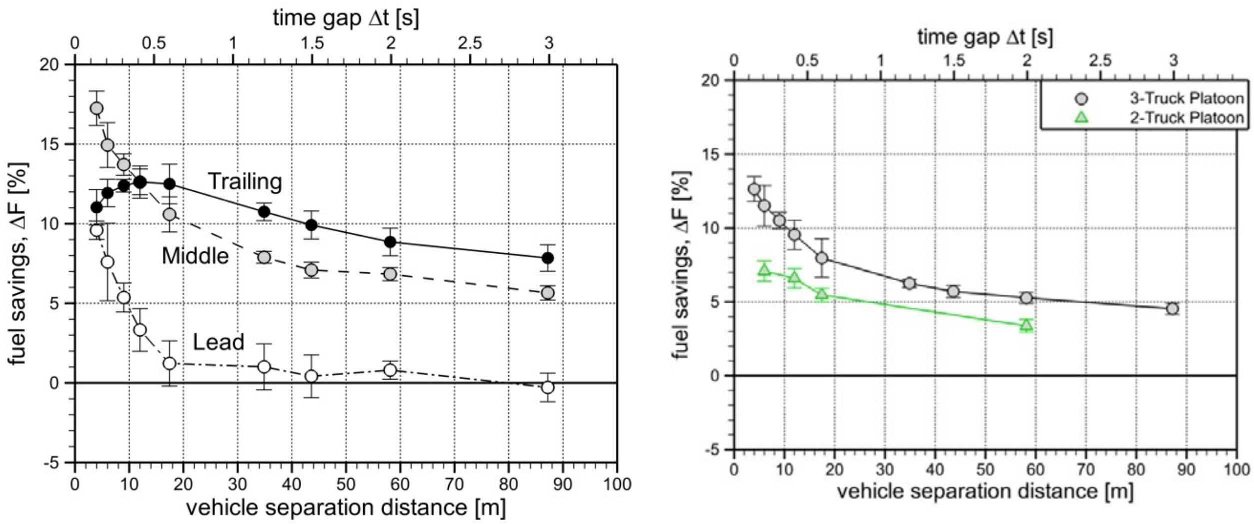


Figure 3-1. Fuel savings for individual trucks as a function of separation distance (left) and average fuel savings for two- and three-truck platoons (right).

Figure 3-1(left) shows the fuel savings for each of the three trucks in the CACC platoon as a function of the separation distance (bottom scale) or time gap (top scale) at a speed of 105 km/h. Note that the lead truck only saves significant energy at gaps of 18 m or less, but the middle and trailing trucks are saving 6% and 8% respectively even as far apart as 87 m. At gaps below 18 m, the relationships become more complicated, with the lead truck's savings rising rapidly toward 10% as the gap decreases to 4 m, and the middle truck's savings rising rapidly toward 17% at the 4 m gap. In contrast, the trailing truck's energy saving peaks at about 13% in the 15 m range and then declines to 11% as the gap is reduced to 4 m. These trends are the consequence of different phenomena affecting the aerodynamics at the front and rear of each truck and are discussed in greater detail in Section 3.1.2. Figure 3-1(right) shows the average savings across the entire three-truck platoon, trending from about 5% at the 87 m gap up to 13% at the 4 m gap. It also shows a similar trend for a two-truck platoon, but with noticeably lower savings, ranging from about 2% less at a 58 m gap to 5% less at a 6 m gap. This indicates the incremental energy saving advantage of extending the platoon length from two trucks to three. Each scenario for the three- and two-truck platoon was repeated three times, and each time for 16 laps (i.e., 16x4 = 64 miles).

The energy savings of the two-truck platoons were also compared to the energy savings potential when the same two trailers are operated in a long combination vehicle (LCV) configuration, pulled by a single truck tractor. The LCV provided an energy savings of 23% compared to two single isolated trucks, three times as much as the savings of the two-truck platoon. However, this does not mean that trucks should take double trailers in order to save energy because, while an LCV does save more energy than two independent tractors and trailers at a constant speed, it is difficult for it to accelerate to highway speed if there is a speed variation. In addition, its maneuverability will be significantly reduced in highway traffic, particularly up hills. Therefore, LCVs will likely form a bottleneck in freeway traffic and significantly affect the overall mobility of the freeway traffic. This degraded traffic performance will increase total delays, total travel time, and speed fluctuations for other traffic, which can easily cancel the energy benefit of the LCVs in the total energy consumption of the overall traffic.

3.1.1.2 Impact of Following Light-Duty Vehicle (SUV) Versus Class-8 Truck

- When following an SUV at a range of 87 m to 43 m, a single Class-8 truck experienced a fuel savings ranging from 1.5% to 2.6%. In contrast, the following truck of a two-truck or three-truck platoon saves on the order of 7.5% to 10%, respectively, at similar following distances.

To investigate the potential fuel savings from operating in the wake of other traffic, as well as to provide a more realistic baseline representing current day "platooning" with mixed on-road traffic, additional tests were conducted with a single truck following an SUV. As can be observed in Figure 3-2 below, at distances from 43 m to 87 m behind the SUV, the single truck experienced fuel savings ranging from 1.5% to 2.6%. In contrast, when following two tractor-trailer combinations at these ranges, the trailing vehicle would experience fuel savings of 7.5% to 10%. In addition to the single vehicle tests shown below, tests were also run with a two-truck and three-truck string following an SUV at 58 m, but those results remain statistically inconclusive and are not discussed in this Capstone report, due to concerns about test-to-test variability in those test conditions.

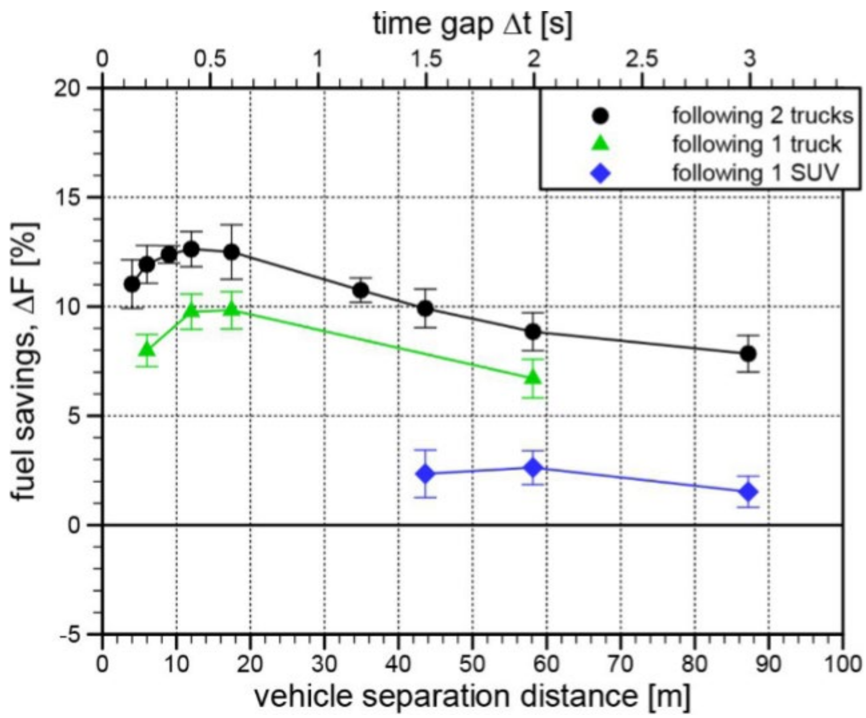


Figure 3-2. Fuel savings of single truck with ACC following an SUV compared to following trucks in two and three vehicle platoons (105 km/h vehicle speed, 29,500 kg vehicle mass).

3.1.1.3 Fuel Consumption Due to Cut-Ins During Platoon Operation

- The effect of traffic cut-ins during CACC operation was found to be only about 2-3% since they were transient behaviors.

To understand the fuel consumption penalty associated with vehicle cut-ins, a problematic issue for real-world CACC/platooning performance, four sets of test runs were performed in which a large SUV periodically cut in between the trucks. All cut-in tests were performed using a baseline CACC configuration with a time-gap of 1.2 s (35 m separation distance at 105 km/h). For each one-hour run, 30 cut-ins were performed at one of the CACC gap locations (between the lead and middle vehicle or between the middle and trailing vehicle). The cut-in vehicle remained in place between the trucks for about 25 to 28 s, during which time the truck following the cut-in vehicle adjusted its position to follow the SUV with a 1.2 s time gap. When the SUV exited the string, the CACC re-established the 1.2 s time gap between trucks. The energy penalties associated with these periods of driving at longer than normal separations with the extra speed changes needed to respond to the cut-ins were encouragingly small. When the cut-in was between the first and second truck, the second truck gave up only 1% of its fuel economy improvement, and when it was between the second and third trucks, the third truck lost between 1.5% and 2.3% of its fuel economy improvement.

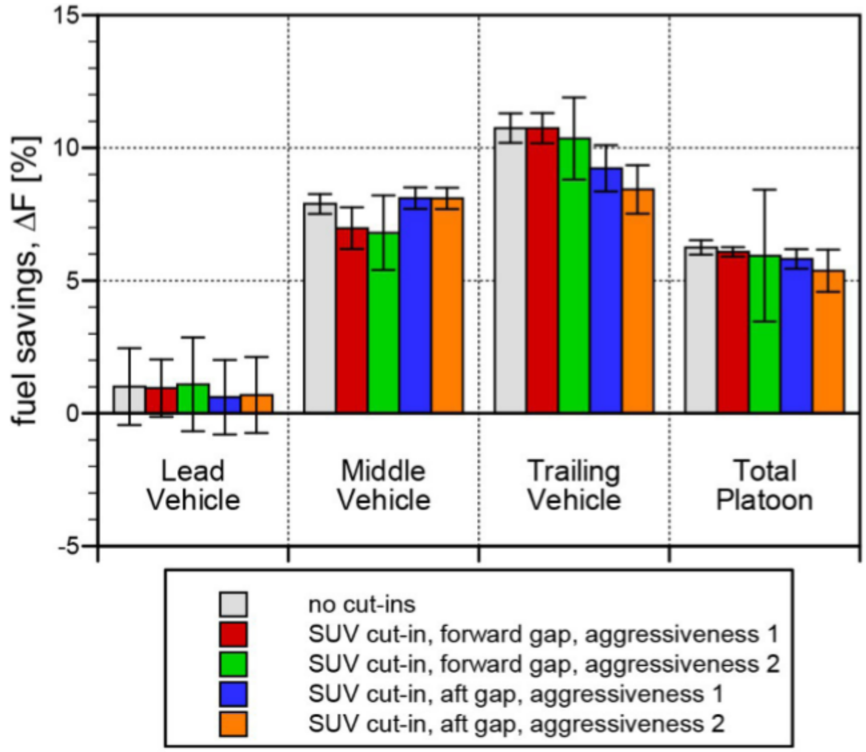


Figure 3-3. Impact of SUV cut-in/out for three vehicle platoons and controller-reaction scenarios (105 km/h target vehicle speed, 29,500 kg vehicle mass).

3.1.1.4 Consumption Impacts of Speed Variations

- At the overall platoon level, the tested speed variations during CACC operation reduced net measured fuel savings for the three-vehicle system to 5.2% from the 6%–7% expected at a 49 m gap distance and baseline 105 km/h driving speed.

In addition to possible cut-ins, CACC trucks in real-world mixed-vehicle traffic are subject to overall traffic speed changes. Therefore, it is necessary to investigate the effect of speed variations on the developed CACC system's fuel saving potential. Testing scenarios used to investigate these impacts included speed variations between 89 km/h and 105 km/h (55 and 65 mph) for the three-truck CACC system at a time gap of 1.2 s, representing a separation distance of 34.9 m at 105 km/h and 29.5 m at 89 km/h. The change in separation distance with speed is due to the time-gap control nature of the CACC. The speed was changed every 100 seconds, with 30 to 40 seconds of constant speed travel before an acceleration or deceleration phase. The results of this test case are shown below in Figure 3-4, with the separation distance variable representing the mean distance and the horizontal error bars representing the range of separation distances encountered over the speed range tested. The test results show a decrease is fuel savings associated with the three-truck CACC system when the periodic speed changes were introduced. Due to the speed variations, approximately 2% lower fuel savings were measured for these variable speed cases than would be expected for this range of separation distances. At the overall platoon level, the introduced speed variations reduced net measured fuel savings for the three-vehicle system to 5.2%, rather than the 6% to 7% expected at this separation distance based on a constant 105 km/h driving speed.

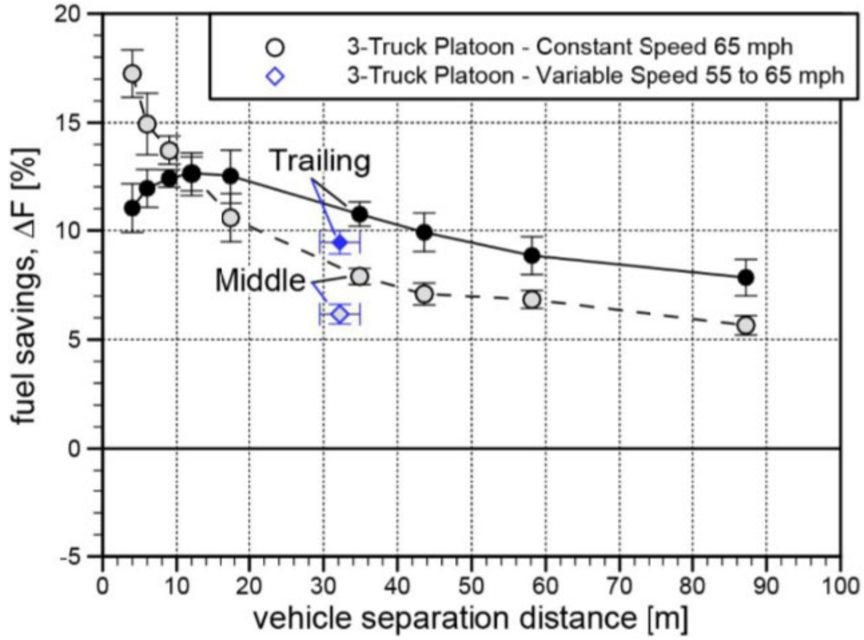


Figure 3-4. Middle and trailing vehicle fuel-savings results for three-vehicle CACC tests with 1.2 s separation time and speed variation (89 to 105 km/h), with changes in speed every 100 seconds. Horizontal error bars represent range of separation distances (29,500 kg vehicle mass).

3.1.1.5 Fuel Measurement Technique Comparison: SAE J1321 versus Fuel Injector Based Measurement

The fuel consumption measurements from the laborious and time-consuming SAE J1321 fuel weighing procedures were compared to simultaneous measurements of fuel injector data from the trucks' data buses, and these comparisons were used to calibrate the data bus measurements so that they could be used for finer-grain assessments of variations within the test runs (not just the total fuel consumption for a complete sequence of 16 laps of the test track). A comparisons of the results from the two methods of measuring fuel consumption are shown in the left plot in Figure 3-5, which shows that the two signals tracked very closely except for the trailing truck at the shortest gap settings.

Figure 3-5 (right) shows how CAN (SAE J-1939) measurements from the fuel injectors can be used to compare the fuel savings on the straight and curved sections of the test track. These results indicate that the savings on the straight sections of the track are about 2% larger than the average savings measured along the entire track. This means that trucks that are driven on essentially straight roads may be expected to save up to 2% more energy from CACC or platooning systems than shown in the results discussed above.

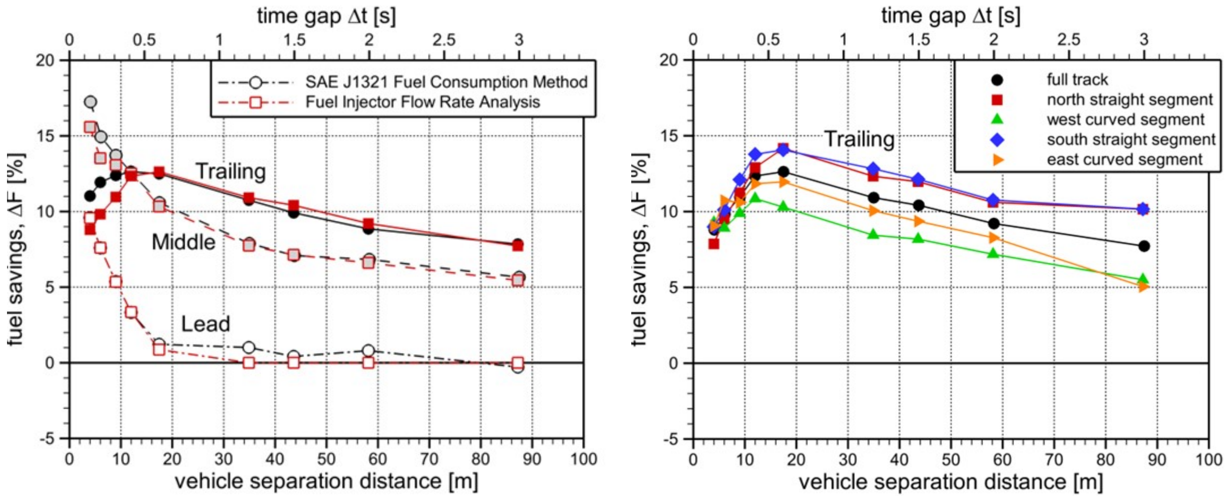


Figure 3-5. (Left) Comparison of J1321 fuel weighing and CAN bus showing fuel injector signal measurements of fuel consumption and (right) CAN bus fuel injector measurements delta fuels savings on straight and curved track.

3.1.1.6 Summary

One potential benefit of a shorter time gap in CACC truck /platooning is energy saving due to aerodynamic drag reduction at higher speeds. The results described here should also apply to CACC platooning-capable trucks with other powertrains, such as hybrid, fuel cell and fully electric. Quantitative tests on a closed test track showed that:

- A truck following another truck at a distance less than 87 m at 65 mph could gain some energy saving benefit, and a shorter time gap saves more energy. For example, a three-truck string saved 11% on average at a 4 m following distance.
- CACC platooning of three trucks saves ~4%–5% more energy than two trucks, so it could be predicted that a four-truck CACC platoon operation could save even more energy. However, this will need confirmation through quantitative tests.
- The effect of other transient maneuvers, such as cut-in and cut-out by other vehicles and speed variation, which are common in real-world traffic, on energy saving is only about 2%–3%.
- At following distances over 12 m, the third truck saves the most and the lead truck saves the least; for distance above 12 m, the middle truck saves increasingly more. The crossing point of this behavior is worth further investigation.

3.1.2 Analysis of Class-8 Truck Platooning Dynamic Air Flow

- For the trailing truck in a platoon, the variability of measured wind speed and wind angle was observed to increase at close following distances, suggesting that increased turbulence (as indicated by the higher variability) is the likely explanation for the reduced vehicle fuel savings demonstrated at close following distances.
- Measured engine and under-hood air temperature increases correlate with vehicle gap distance and platoon position and will inform vehicle and engine thermal control design.

The work described in the previous section has shown significant fuel-savings promise for a range of truck platooning strategies but has also raised unexpected questions about the air-flow effects of these strategies on aerodynamic drag and engine temperatures. To support research into these questions, additional onboard instrumentation was installed on the experimental vehicles to help the team gain a deeper understanding of the air-flow dynamics and interactions between multiple vehicles.

Specifically, the following instrumentation methods were used to understand air flow and engine temperatures, in addition to the fuel consumption-based instrumentation discussed in the previous section:

- J1939 CANBUS[32] native data stream capture
- Cobra Probe[33] mounted 1 meter ahead of vehicle and 2 meters from the ground (Figure 3-6, left)
  - Probe provides three-component velocity and local static pressure plus an ambient temperature thermocouple.
- Air velocity transmitter mounted flush to center of grill (Figure 3-6, right)
  - Transmitter provides air-flow velocity and temperature of air entering the engine compartment.
- Six-thermocouple grid attached under hood with air gap between it and the hood surface
  - Grid provides under-hood temperatures during platooning operation under various testing conditions.

Figure 3-6. Supplemental airflow instrumentation from truck platooning experiments: (left) Cobra probe mounted 1 meter ahead of vehicle and 2 meters off the ground, (right) air velocity transmitter mounted flush to center of grill.

To explain the reduced savings at close following distances for the last vehicle in a platoon, detailed data analysis was performed using the additional information collected from this instrumentation during the track testing for these cases: 1) air flow experienced by the following truck along with turbulence changes at the close following distances where reduced trailing vehicle fuel savings were observed, 2) impacts of platooning position on engine cooling in different formations due to reduced air flow through the front grill (ram air), 3) a true in-use aerodynamic “baseline” with other light-duty vehicles on the highway, and 4) correlation between track test data and wind tunnel-derived average drag coefficient, pressure and particle image velocimetry data.[34,35] The CAVs Pillar’s detailed data analysis approach includes harmonic analysis of wind speed and direction while utilizing J1939 CANBUS data from the 2017 track test to investigate air flow and turbulence changes affecting the following truck.

Data analysis indicates that many of the data trends in wind angle, wind speed, turbulence and temperature show a non-linearity in pattern for closer following distances, where a fuel savings decrease for the following vehicles was also documented. Figure 3-7 illustrates the magnitude and angle of wind experienced by each truck in a platoon over a range of distance. Note that while the lead vehicle always has a mean speed of 29 m/s (65 mph), the following trucks start to see significantly slower speeds and higher angles of wind when closer than 35m. At distances of 12m and less, the radar plots take on an arrowhead shape — indicating high variability in both angle and speed — and this turbulence correlates with the distances at which following trucks exhibit an unexplained drop in savings.

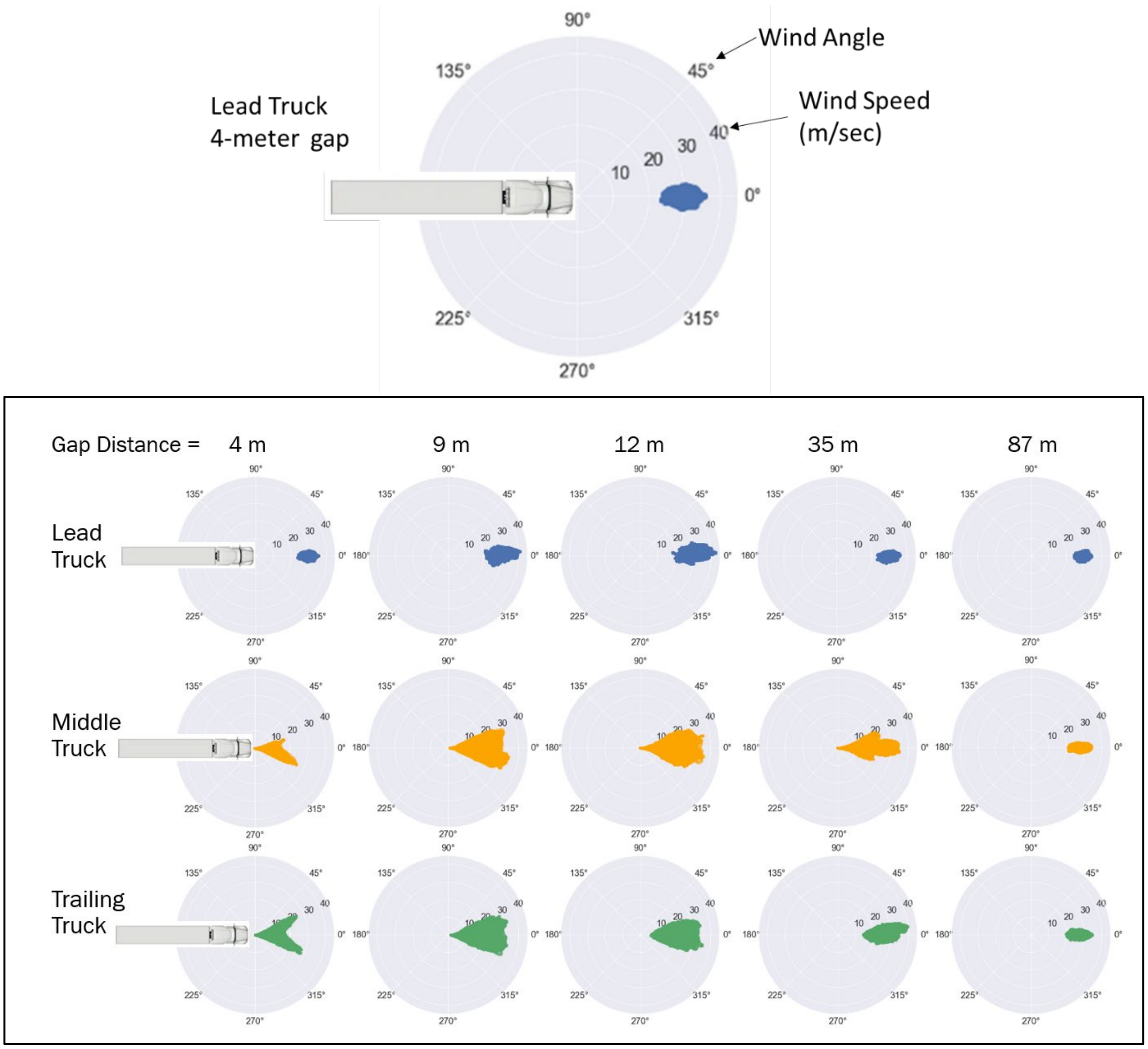


Figure 3-7. Magnitude and angle of wind radar plots.

Results of the thermal analysis show that significant changes in the engine and under-hood air temperatures correlate with vehicle gap distance and platoon position. Figure 3-8 shows the significant temperature increase from ambient for following vehicles, especially at gap distances less than 20 meters.

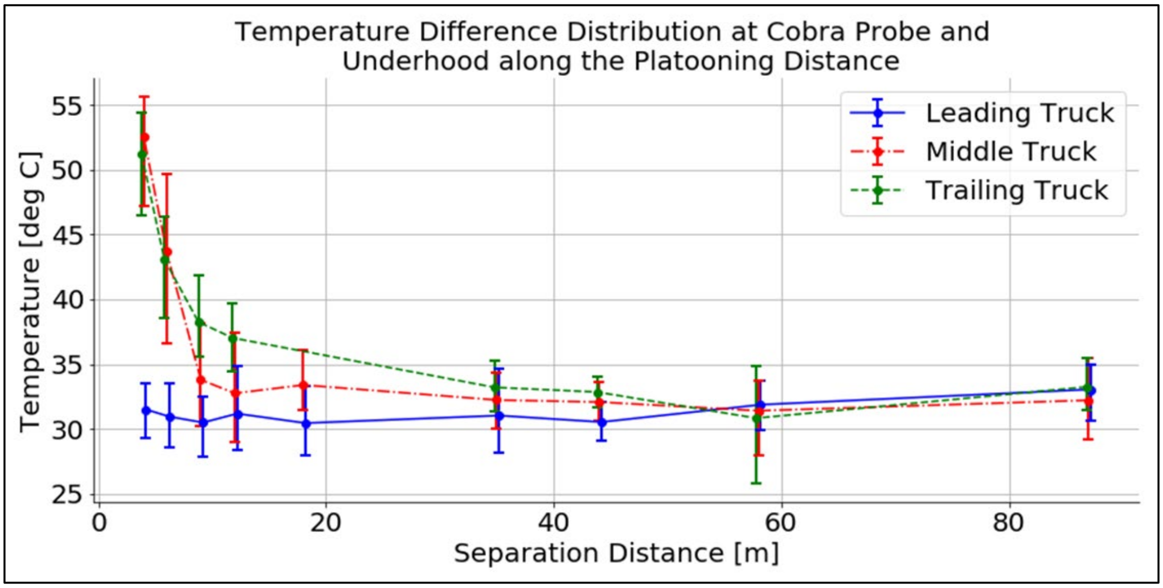


Figure 3-8. Temperature difference at varying separation distances.

These results are encouraging. A similar analysis of the SUV and dynamic cut-in scenarios could yield insights into the fundamental cause of the reduced savings. Analysis of the baseline scenarios with SUVs would refine the findings from the standard platooning scenarios and allow for investigation into the fundamental problem.

3.1.3 Understanding Realistic Class-8 Truck On-Road Platoon Opportunities

- Two studies with different data sets and methodologies conclude that 63–66% of class 8 truck miles are at speeds where platooning would achieve aerodynamic benefits demonstrated in track test conditions.
- One study concluded that for an early adopter subset of vehicles, 77% of miles are platoonable.
- One study using telematics data from 57,000 unique Volvo trucks concluded that 56% of classifiable miles were both at platoonable speeds and had a partner vehicle from the same fleet of 57,000 available for platooning (usually multiple partners were available).

While the fuel savings opportunities related to Class-8 truck platooning discussed in this document are promising for close following/platooning vehicles equipped with cooperative adaptive cruise control (CACC) operating in highway environments, many unknowns can influence the actual savings during real-world operation. Specific to this investigation are: 1) time spent at speeds appropriate for observable aerodynamic benefits and 2) the availability of a partner vehicle to platoon with.

A preliminary study to estimate the fraction of "platoonable" miles[36] was based on a large set of driving data: more than 3 million miles of high resolution driving data from 194 tractors in NREL's FleetDNA database.[37] The data were collected using on-board data logging devices or telematics systems. Vocations represented in the data include line-haul truck load, less than truck load, regional parcel movement, port drayage, refrigerated operations, tanker operations, transfer truck operations, and regional food delivery. The data set includes information on vehicle speed (1-second resolution), GPS position, road segment (highway, freeway, or collectors and local), and various levels of engine/vehicle parameters, such as fuel rate and engine temperatures. Platoonable mileage was estimated by analyzing highway vehicle use and prolonged high-velocity travel.

Results of this analysis are shown in Figure 3-9. The upper plot shows the share of miles driven over each road segment type based on the entire data set, as well as the fraction of miles continuously driven for given minimum time durations above a range of vehicle speed thresholds. For instance, the results show that for a time threshold of *T*= 15 minutes at a speed threshold *V* = 50 mph, 66% of vehicle miles are platoonable (and show how this number changes at different time and speed thresholds). The same methodology is applied to a subset of the data that might represent early adopters of this technology, including approximately 4,500 miles of mostly highway long-distance driving to evaluate the fraction of platoonable miles for specific applications. The vocation represented for the early adopter subset is a split-duty combination truck that runs local pickup and delivery trips during the day and regional line-haul operation at night (representing the majority of the miles driven and making this application well suited for platoon operations).

Results for this early adopter subset of highway-centric data, shown in the lower plot in Figure 3-9, indicate that for a time threshold of T = 15 minutes and a speed threshold V = 50 mph, 77% of vehicle miles are platoonable. This technical potential for platoonable miles in the United States helps provide an upper bound for scenario analyses quantifying the overall potential fuel savings benefits of truck platooning.

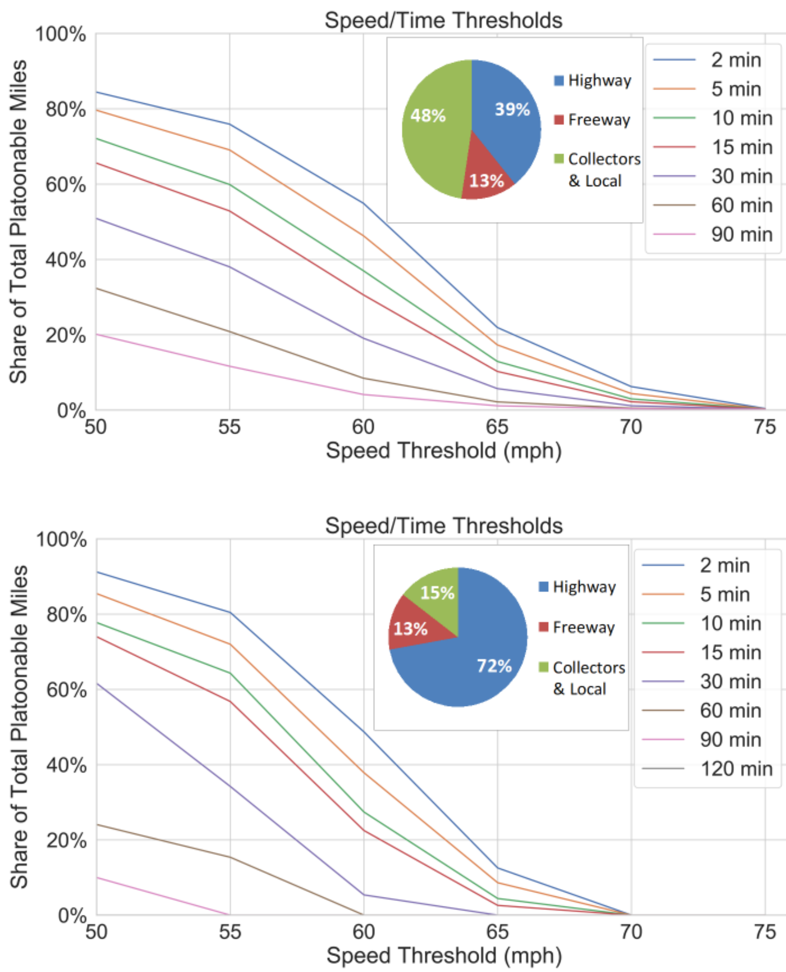
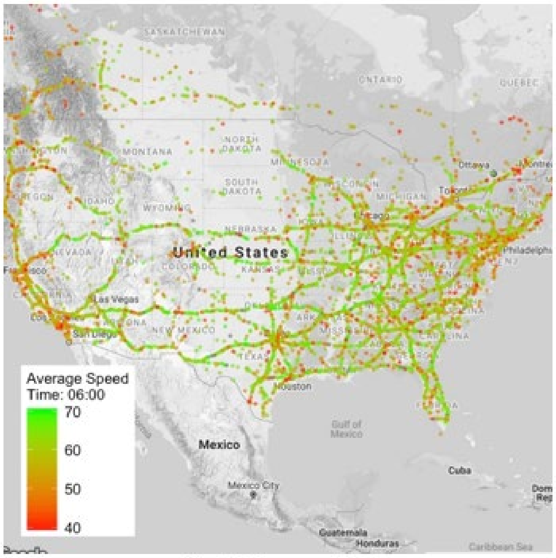


Figure 3-9. Share of total miles (y-axis) continuously driven above a certain speed threshold (x-axis) for T minutes that are platoonable for share of load segments, considering the entire data set (upper) and a select highway-centric targeted likely early adopter subset of entire dataset (lower).

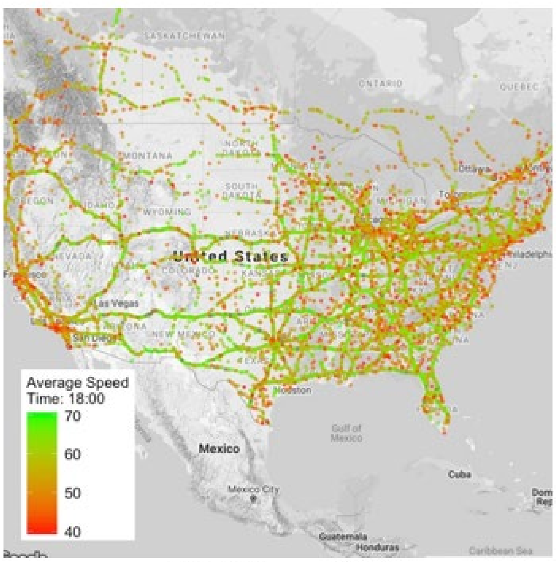
A second study[38], in collaboration with Volvo Trucks North America, analyzed a two-week period of Volvo Trucks' telematics data from over 57,000 unique vehicles traveling more than 210 million miles, which included 11 million GPS waypoints, during the summer of 2016. Telematics data from this study were also used to identify opportunities in which both a partner vehicle and acceptable operating conditions were observed. Despite covering a large population, these data have very low time resolution, consisting primarily of hourly observations of the vehicles throughout the day. Therefore, specific duty cycle understanding is limited to knowing what probably happened over the course of the hour, as average vehicle speeds are based on the odometer change between observations. The data does indicate that 75% of total fuel consumption occurs when the trucks operate in top gear, suggesting heavy highway utilization (and significant potential platooning fuel savings opportunities).

Figure 3-10 shows the geospatial representation of hourly average speed for all active trucks in the dataset at different times during a weekday. Overall, more trucks travel on the road network during daytime hours than during the night or early morning. However, travel speeds during night operation are generally higher than in day operation due to lower nighttime traffic volumes. Figure 3-10 also indicates that the East Coast, West Coast, and urban areas have higher temporal variability than the central part of the country. Analysis using a highway speed based method similar to the one used in the previous study suggests that 63% of total miles driven at known hourly average speeds may have potential for platooning.

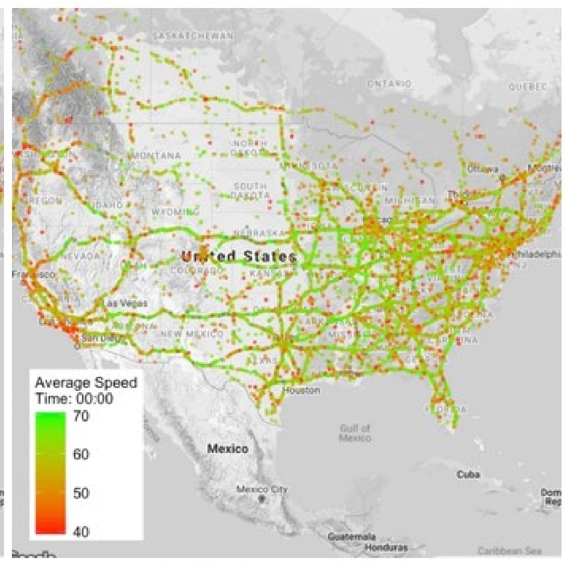


(a) 6:00 am – 7:00 am

(b) 12:00 pm – 1:00 pm



(c) 6:00 pm – 7:00 pm



(d) 12:00 am – 1:00 am

Figure 3-10. Geographic representation of hourly average speed at different times of day.

When considering the availability of nearby[iii] (Volvo) partner vehicles, results indicate that 56% of all classifiable miles driven were platoonable. Further, the platooning opportunity potential would be greater if inter-manufacturer platooning were to be considered. Figure 3-11 shows a snapshot of the spatial distribution of these partner availability based platoonable observations for a single day. The patterns evident in Figure 3-10 are also present here. The highest regions of platoonability occur across major shipping corridors and interstate highways. Urban areas, particularly those in dense regions on the East Coast and West Coast and in the Great Lakes region, appear to have fewer opportunities than West and Midwest regions, though lower speed limits in West Coast states were not taken into consideration.

[iii] Where "nearby" means traveling at least 50 mph AND within a 15-mile radius and 15-minute travel time window.

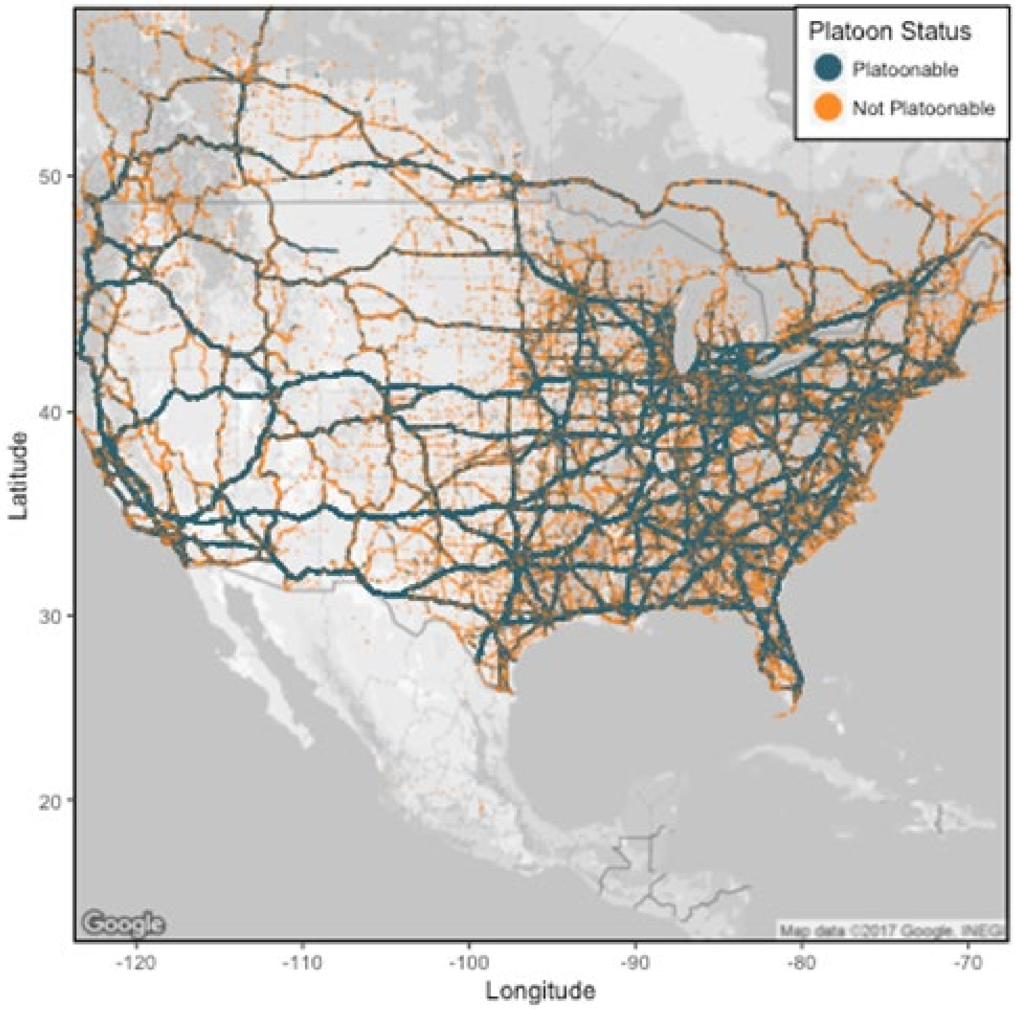


Figure 3-11. Snapshot of U.S. platoonability based on partner analysis for a single day. Observations with speeds less than 30 mph are omitted for clarity.

Figure 3-12 shows the available platooning partner distributions for the platoonable cases. In most cases, multiple partners could be available to platoon, with a peak occurring at around 2-3 partners and a mean of 10. This indicates that it could be worthwhile to investigate the opportunity for 3- and 4-truck platoons, and that fleet non-cooperation and technology incompatibility would have minimal impact on partner availability for 2-truck platoons.

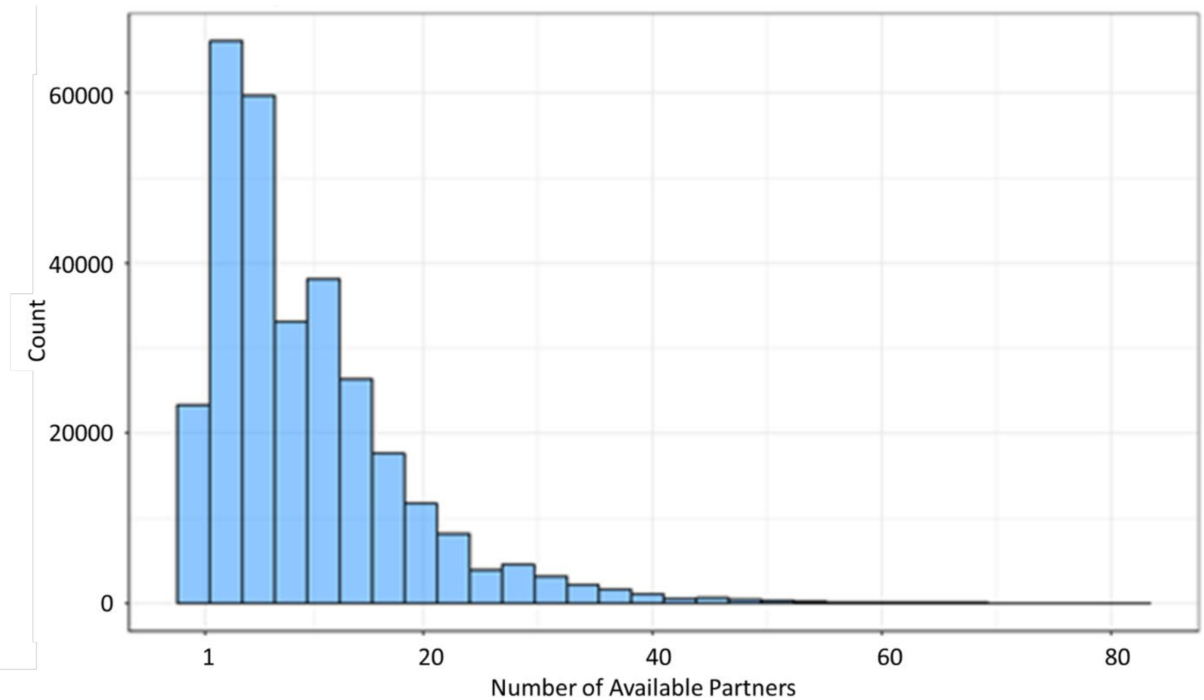


Figure 3-12. Distribution of number of available platooning partners.

Comparing results from the two studies shows that the proportion of platoonable miles traveled for known data aligns with the overall spatial patterns of partner availability, suggesting that the computationally simpler vehicle speed method from the first study may be sufficient for high-level platooning analysis. The detailed availability information gathered from the proximity analysis in the second study provides additional context and will be critical for more advanced analysis of adoption scenarios where different platooning systems are incompatible, or fleets do not have platooning cooperation agreements in place. The proximity analysis also provides decision makers with information on the value of platooning technologies capable of connecting more than two trucks by identifying how often larger platoons could be formed. Additional partner characteristics such as vehicle type, load, origin/destination, etc. could be included in future analyses but were omitted here.

Combined with the truck platoon team fuel savings potential demonstrated in the track testing scenario analysis reported in Section 3.1.1, the substantial opportunities for Class 8 truck platooning identified by these results suggest that truck platooning could be an effective fuel saving strategy nationally. Combination trucks drove 174 billion miles in 2016, consuming 29.6 billion gallons of fuel. If the nation's truck fleet were to save 6.4% of fuel with conservatively spaced 2-truck platoon teams for 56% of the miles traveled, the overall reduction in fuel consumption would be on the order of 1.1 billion gallons of fuel per year (roughly 0.5% of U.S. transportation energy use in 2016) resulting in 10.7 million metric tons of CO_2 reductions. Platoons of three close-following trucks achieving a combined 13% fuel consumption reduction would save close to 2.1 billion gallons of fuel per year.[39]

These studies demonstrate the value of both high-resolution data and more traditional low resolution telematics data sets. Despite leveraging data with very different time steps, both studies found that 63%–65% of Class 8 tractor miles occur at speeds that can realize the aerodynamic benefits of truck platooning, while target early-adopter vocations may have as much as 77% of their miles available for platooning fuel savings. Intra-manufacturer availability restrictions may reduce this mileage percentage by roughly 10%, but cross-manufacturer platooning would likely make up much if not all of that difference. More detailed fleet- and manufacturer-level cooperation scenarios will be necessary to further refine these high-level studies as well as identify specific fleet types/vocations that will outperform the population analysis done to date.

3.1.4 Objective Method to Quantify On-Road CAV Fuel Efficiency — Demonstrated on In-field Assessment of Large-Scale, Light-Duty Adaptive Cruise Control (ACC) Fleet Pilot Data

- A novel method for estimating overall on-road energy impacts from specific CAV technologies was developed and demonstrated in partnership with Volvo Cars Corporation.
- In today's traffic mix, vehicles operating with adaptive cruise control saw 5%–7% lower fuel consumption at the vehicle level than fully manually driven vehicles.
- However, with high CAV penetration, cooperative adaptive cruise control will be important in maintaining benefits for both individual vehicles and the overall traffic flow.

Overall on-road fuel efficiency of CAV technologies can be difficult to quantify, as the fuel efficiency of a given CAV technology compared to a fully human-controlled vehicle can vary in different driving contexts. The CAVs Pillar developed a methodology that evaluates the fuel efficiency difference between a CAV technology and manual driving in a wide array of driving conditions or contexts and quantifies the overall impact by weighting the specific driving context fuel efficiency differences by the amount of driving that occurs in each context.[40] In collaboration with Volvo Cars, application of this methodology in a partial automation technology context was demonstrated over a large on-road dataset of vehicles operating with and without active adaptive cruise control (ACC). While multiple studies[41,42,43] have identified fuel-saving potential from ACC strategies, the literature remains limited in terms of real-world operational and energy-consumption differences between this type of automated driving behavior and comparable manually driven vehicles under various driving conditions. The Volvo Cars collaboration helped to fill this information gap and explored the proposed methodology's potential to quantify overall CAV technology on-road fuel efficiency — an objective of interest to Volvo Cars not only for ACC but also for higher-level CAV technologies being contemplated under the "Drive Me" project.[44] The designated Drive Me project driving route covered 40 km of major roadways around Gothenburg, Sweden, typical of commuting conditions where customers would be anticipated to benefit from vehicle automation. Data for the ACC versus non-ACC fuel efficiency comparison were collected from vehicles traversing various portions of this designated route[45,46].

For this research, Volvo diesel automatic models (V70, XC70, V60) were driven by Volvo Cars employees and family members on more than 18,590 trips over the Drive Me route during the 2010–2011 project timeframe. Vehicles were equipped with ACC that used a radar sensor to detect the distance to the vehicle ahead and adjusted the ACC-equipped vehicle's speed to maintain a preferred gap between the vehicles. Fuel consumption data, reported to be of good quality by Volvo Cars, were collected from the vehicle's data bus at a 10-Hz sampling rate. Additional data included vehicle and engine speed, pedal positions, GPS position, ACC status, and distance to the nearest leading vehicle, along with ambient temperature and weather conditions. Available traffic and driving condition data over the Drive Me route included the number of vehicles passing 130 fixed traffic detector locations, the traffic speed (which varies with time of day and day of week), and the road grade (which can significantly impact the fuel consumption of the test vehicles). This work builds on a preliminary fuel consumption analysis done by Volvo, and expands upon that effort by creating the framework in which fuel consumption impacts under different driving conditions are weighted to obtain an estimated aggregate impact at the road-network level. As described in much greater detail in the corresponding publication[47], the analytical methods applied for these efforts included:

Step 1: Separate ACC from non-ACC trips
Step 2: Separate trips into segments and map-match
Step 3: Segregate data by driving conditions and calculate statistical significance
Step 4: Create fuel consumption rate ratio matrix across relevant driving condition dimensions and perform any rate adjustments where needed

Step 5: Prepare traffic flow data and perform traffic flow modeling to fill in any gaps
Step 6: Create corresponding vehicle miles traveled (VMT) matrix
Step 7: Calculate aggregate ACC impact

The first step in the process was to separate ACC from non-ACC trip data based on whether vehicles had ACC on or off. Next, the trips were separated into segments of 0.5 km or shorter, and these segments were matched to road links on a base map. The segment data were categorized by road grade and by the average traffic speed at the time of travel to enable comparison of the two vehicle modes under common operating conditions. Traffic speed was estimated using the average road link speed at time of travel based on historic TomTom Traffic Statistics data, when available. When these data were not available, the average traffic speed was represented by the average speed from the test vehicle's GPS trace. The above methods were then utilized for characterizing ACC and non-ACC vehicle operation and fuel use as well as weighting ACC fuel economy improvement by driving condition and VMT.

The sample of ACC driving data contained significantly fewer low-speed driving segments than in the non-ACC data. According to Volvo Cars, ACC could only be activated at speeds above 30km/h, which no doubt contributes to this difference. However, the ACC driving data did include some segments with driving speeds below 30 km/h, so ACC evidently remains active at these speeds if it is turned on at a higher speed before traffic conditions force the vehicle to slow. Focusing on driving segments in traffic conditions ranging from 40 to 110 km/h (where the vast majority of the ACC and non-ACC sample data occur), Figure 3-13 compares acceleration standard deviation distributions for each driving mode. Higher acceleration standard deviation indicates more rapid changes in vehicle acceleration and would be expected to correlate with higher fuel consumption compared to smoother driving with lower acceleration standard deviation. The figure shows comparisons for the standard deviation of both acceleration and deceleration rates for ACC compared to non-ACC mode, with the results indicating overall smoother driving behavior from ACC operation: The average acceleration/deceleration standard deviation in ACC mode was +0.22/-0.21 m/s^2 compared with +0.29/-0.29 m/s^2 in non-ACC mode.

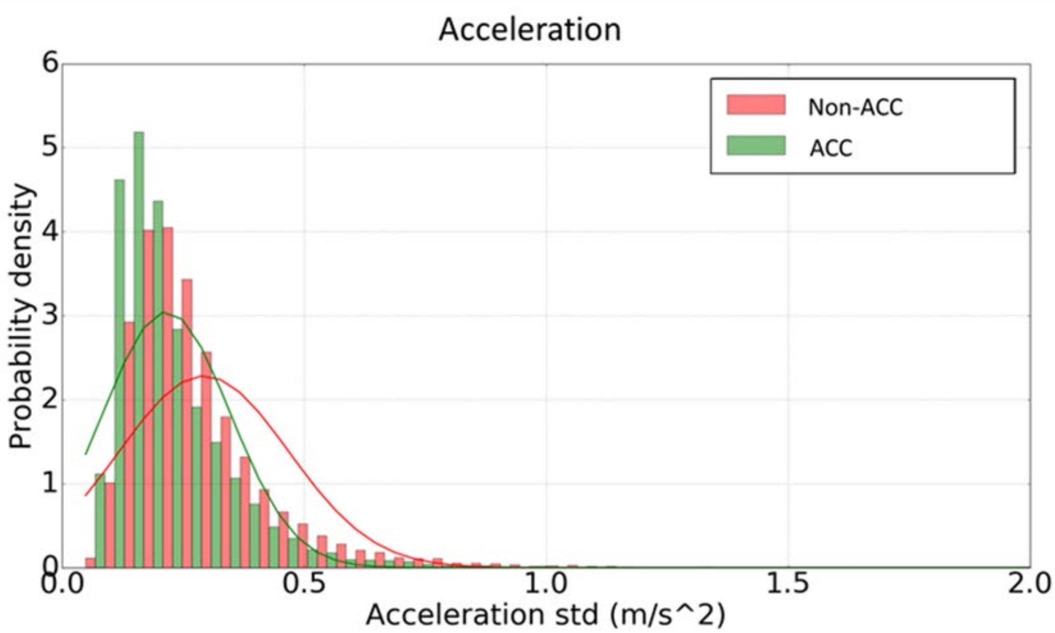


Figure 3-13. Distributions of acceleration (top) and deceleration (bottom) standard deviations in ACC and non-ACC mode.

Consistent with the overall smoother driving behavior observed for the vehicles in ACC mode, ACC operating vehicles tended to show lower fuel consumption rates than non-ACC operating vehicles across most driving conditions. Figure 3-14 illustrates the estimated annual distribution of all vehicle travel that occurs on the designated driving network in each combination of traffic speed and road grade condition. An adequate amount of on-road data to determine statistically significant fuel consumption rate differences between ACC and non-ACC driving were collected in many, but not all, of these driving condition bins. Fortunately, albeit unsurprisingly, the best coverage coincided with the driving condition bins where most network travel occurs. This mitigates but does not completely eliminate the problem of dealing with driving condition bins that experience a measurable level of vehicle travel but lack a statistically significant measure of the fuel consumption rate difference between ACC and non-ACC operation. To resolve this issue, several sensitivity scenarios were conducted, including ignoring these bins, setting various fixed ACC/non-ACC fuel consumption rate ratios for these bins, and interpolating "educated guess" ratios based on nearby bins with statistically significant measured values. Vehicle travel distance weighting over all of the driving condition bins was performed for each sensitivity scenario to generate a robust ACC fuel efficiency impact estimate over the evaluated driving network.

Speed Bins (kmph) / VKT (unit: million)	% Grade Bins (-5, -4]	(-4, -3]	(-3, -2]	(-2, -1]	(-1, 0]	(0, 1]	(1, 2]	(2, 3]	(3, 4]	(4, 5]
(0, 10]	0.03	0.12	0.15	0.13	1.73	1.31	0.42	0.19	0.04	0.02
(10, 20]	0.22	0.19	0.50	0.82	4.86	5.59	1.16	0.64	0.10	0.09
(20, 30]	0.48	0.70	1.38	1.57	9.03	9.44	1.90	1.22	0.17	0.15
(30, 40]	0.78	0.88	1.98	2.05	13.19	12.13	2.95	2.14	0.35	0.44
(40, 50]	1.21	1.49	3.38	3.23	23.32	19.45	3.63	3.64	1.09	0.94
(50, 60]	3.67	4.69	8.54	8.19	51.73	34.90	8.74	9.70	4.60	2.24
(60, 70]	9.90	13.73	19.48	32.11	130.93	89.55	33.02	28.82	17.10	6.74
(70, 80]	9.04	14.16	28.23	50.57	214.64	164.88	62.58	27.19	15.78	7.89
(80, 90]	4.05	5.25	15.02	23.26	229.98	152.27	30.53	7.76	4.71	1.58
(90, 100]	0.62	0.64	5.49	6.18	161.99	87.78	11.52	1.35	0.59	0.21
(100, 110]	0.07	0.09	0.49	0.61	28.44	18.98	1.55	0.32	0.08	0.03

Figure 3-14. Variation in estimated overall annual vehicle travel on the designated driving network in Gothenburg (in millions of vehicle kilometers travelled) organized by speed and grade bins (high values in red/orange, moderate in yellow and low in green).

The vehicle travel distance weighting and sensitivity scenario evaluation process revealed that these ACC-operating vehicles consumed 5%–7% less fuel than the fully manually driven vehicles over the designated driving network. Other considerations for automated vehicle fuel use include their types/specific implementations and penetration levels in traffic. For instance, while the ACC vehicles in this Volvo Cars study operated mostly around surrounding vehicles with the driver in complete control, other studies have shown that many ACC vehicles operating together can make traffic worse, due to the lag for each vehicle to detect speed changes in the others.[48] It is possible for high automation penetration to improve rather than worsen overall traffic flow if it includes vehicle-to-vehicle communication, enabling Cooperative ACC (i.e., CACC — see the SMART Mobility work described in Section 3.3.1 of this CAVs Capstone Report).

The fuel economy calculation approach featured in this study can be applied to simulations of hypothetical future technology penetration scenarios as well as to data from the latest vehicle technologies operating in current traffic conditions. With automated vehicles possessing enhanced data collection and connectivity capabilities, the proposed approach could provide increased visibility into how on-road fuel economy evolves with changes in vehicle technology, penetration rates, and traffic impacts. Such transparency is important for stakeholders and policymakers who wish to measure technology impacts on transportation energy use and for automakers who wish to get credit for potential fuel-saving features of automated vehicle technologies.

3.1.5 Experimental Evaluation of Eco-Driving Strategies at Intersections

- The data collected during the EAD field testing shows a moderate fuel savings of 10% to 20% as compared with adjacent vehicles without EAD operating in an 80m zone centered at the controlled intersection (i.e. 40m before, 40m after). However, within this field testing, the frequency for encountering EAD scenarios is low, making the overall benefits at the trip level insignificant.

- Experimental testing on the dynamometer has confirmed that for recent conventional vehicles the simulation values from literature for highlighted EAD benefits are relatively in-line with the experimentally observed benefits, but the benefits and sensitivities of the EAD strategies evaluated diverge significantly for electrified vehicles with some strategies providing a greater impact for electrified vehicles and some strategies showing less benefit due to the already more efficient operating capabilities of electrified vehicles.
- Field data taken during the EAD intersection testing for a specific intersection, showed that for vehicles stopping at this intersection, over 80% of the time they do not encounter other vehicles at the conflicting approach. These unnecessary stops are the primary cause of unproductive fuel consumption at signalized intersections, which accounts for over 15% of total estimated fuel consumption at this test intersection during observation. This suggests that, for the intersection assessed during this work, more intelligent signal operation supported by connected vehicle and connected infrastructure technologies could lead to additional fuel consumption benefits due to reduced stops.
- For the stop-sign controlled intersection assessed for this work, the majority of vehicles arrived at the intersection without encountering a vehicle at the conflicting approach (68% at the test intersection), suggesting that additional benefits could be achieved with improved coordination via the reduced need for stopping.

Studies on Eco-Approach and Departure (EAD) at intersections account for a large percentage of the reported studies on the broader topic of Eco-Driving. The reported benefits from various studies on specific Eco-Driving strategies vary significantly, with fuel savings ranging from 2%–3% to 50%.[49,50,51,52] Most of the existing EAD studies rely on analysis and simulation to demonstrate the effectiveness of specific algorithms. Fewer studies involve analysis of field or laboratory data collected in real-world situations with real vehicles. As many previous studies focused on searching for optimal solutions, the findings also often highlight the best possible performance and resulting maximum benefits as opposed to a range of performance over varying conditions. Furthermore, the baseline assumptions and model calibrations reported in these studies vary significantly, and the research results are often not easily comparable. For studies that include experiments, data are sometimes collected under specific, tailored operational scenarios in which the maximal fuel savings can be demonstrated. For example, field testing of EAD without traffic represents one of the most desirable operating conditions and results in much greater fuel savings than one may expect in the real world. There is a need for realistic energy saving benefit estimates using field and laboratory data collected under a wider range of operational scenarios in real-world situations across a range of vehicle powertrain technologies.

Under the SMART Mobility program, a system-level analysis quantified the extent of unproductive fuel consumption at intersections at the national scale and identified and evaluated opportunities to address the causes of unproductive fuel consumption. Unproductive fuel consumption for intersections is defined as the unnecessary fuel consumption of vehicles that are directed to stop when neither vehicles nor pedestrian activities are present at the conflicting approaches. In this work, highlighted connectivity and/or automation-based EAD strategies for intersections were analyzed and experimentally evaluated for potential and realistic benefits. Specifically, three experimental studies were conducted to realistically estimate fuel savings for specific EAD strategies, including (1) laboratory experiments to assess the scenario-based fuel saving benefits of EAD for different types of powertrain technologies, (2) field testing the fuel saving benefits of EAD advisory information at signalized intersections in real-world traffic conditions, and (3) evaluation of unnecessary stops and subsequent unproductive fuel consumption at signalized and unsignalized intersections.

3.1.5.1 Analysis of Unproductive Fuel Consumption at Intersections

The Urban Mobility Report (UMR) by the Texas Transportation Institute[53], a widely referenced estimation of wasted fuel and travel time due to congestion, estimates that 3.1 billion gallons of fuel are wasted annually. However, the UMR did not consider many non-congestion related factors that cause fuel waste. The average nature of the data used in the UMR analysis is adequate for defining the problem the nation faces in wasted fuel and excessive emissions due to congestion, but the estimate of wasted fuel at intersections is not precise because of the assumption that stop-and-go behaviors at signalized intersection are equivalent to low average speeds. Further analysis shows that controlled vehicle stops at signalized intersections when no vehicles or pedestrians are present at conflicting approaches also results in unproductive fuel consumption, which is not accounted for in the UMR study. The extent of unproductive fuel consumption at signalized intersections depends on many factors and certain specific components and sensitivities are investigated experimentally in this study. The CAVs Pillar researchers also investigated unproductive fuel consumption at stop sign controlled intersections and revealed that substantial fuel is consumed unproductively for vehicles making stops when no vehicles are present at conflicting approaches. Field data collected at both signalized and unsignalized intersections, described below, provided scientific evidence to support further assessments of unproductive fuel consumption at intersections.

3.1.5.2 Laboratory-Based Investigation of Select Eco-Driving Approaches

- Experimental dynamometer testing has confirmed that for recent conventional vehicles, simulation values from literature for highlighted EAD benefits are relatively in line with experimentally observed benefits. However, the benefits and sensitivities of the EAD strategies evaluated diverge significantly for electrified vehicles with some strategies providing a greater impact for electrified vehicles and some strategies showing fewer benefits, due to the more efficient operating capabilities of electrified vehicles.

For this work, the potential eco-driving benefits of select intersection approach trajectories for two distinct scenarios were evaluated across four different powertrain types in a dynamometer-based laboratory environment. The two intersection approach scenarios considered in this study were: 1) an approach to a red light where stopping is not needed, given a proper trajectory recommendation and 2) an approach where a complete stop is needed but known in advance due to information provided from I2V communications. The four powertrain types tested in this study included a conventional vehicle, a conventional vehicle with idle stop-start, a hybrid electric vehicle (HEV), and a battery electric vehicle (BEV). The test vehicles used for this study were a 2017 Ford F150 with a 3.5L V6, 10-speed automatic transmission, and stop-start capability (conventional and start-stop cases) and a 2017 Toyota Prius Prime PHEV (HEV and BEV case due to its full engine-off capability). To ensure test-to-test repeatability, driving was done by a robotic driver following the desired computed approach trajectories. More detailed specifications for each vehicle as well as the instrumentation and experimental setup can be found in in the research publication related to this work.[54] The test cycles evaluated for this work comprised a series of intersection approach and launch speed traces referred to as Approaches 1-4, and were based on two different simulation studies found in the reference literature (Scenario 1 and Scenario 2, respectively).[55,56] The results of these literature-based reference simulation studies for conventional vehicles, are the “reference values” in the results displayed in this section. Results from each experimental scenario studied on the dynamometer are compared to the reference value, in the applicable simulation study.

Scenario 1, shown in Figure 3-15, is a vehicle approaching an intersection where slowing down is necessary but a full stop is not required (short red light). The EAD strategy investigated, based upon the first literature reference, involves an on-board calculation of the cruising speed and associated initial deceleration profile that would make the vehicle reach the intersection just after the signal changes back to green.[57] Then, once the vehicle enters the intersection with a green light signal, it accelerates back up to its previous cruising speed. Approaches 2 through 4 apply this cruising-based EAD strategy (using knowledge of the signal timing to identify a cruising speed). However, in Approach 1, the vehicle decelerates continuously to the stopline, although it is still aware of the impending phase change due as shown by its non-zero arrival speed at the stop line. Experimental results comparing the additional benefits of Approaches 2 through 4 over Approach 1 for the different powertrain technologies included in this study are discussed below.

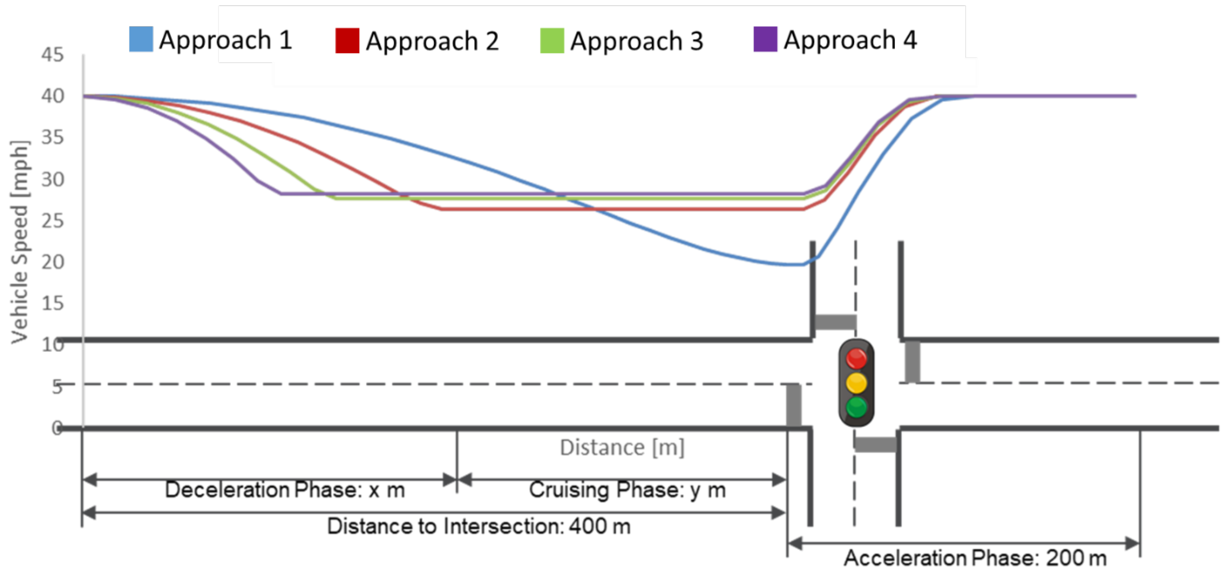


Figure 3-15. Intersection eco-approach and launch with no stop required (Scenario 1).

Figure 3-16 summarizes the relative additional consumption improvement for Approaches 2 through 4, over Approach 1 for the various powertrain configurations compared to the reference value for this strategy from the literature source. Results for the stop-start enabled vehicle are not shown since they are identical to the conventional vehicle results, because neither stopped in this scenario. For the conventional vehicle, Approach 2 was observed to have minimal additional fuel consumption benefit compared to Approach 1, while Approaches 3 and 4 showed additional benefits of 5% and 3%, respectively. When applied to the HEV and BEV powertrain vehicles in this study, the cruising-based EAD strategy showed additional consumption benefits over Approach 1, with slightly increasing benefits from Approach 2 to Approach 4. The simulation-based results in the original reference work also show an increasing benefit between Approach 2 and 4; however, the absolute value of the reference result is significantly higher than the experimental test results for any of the three powertrain types. It is also interesting that the experimental test results for the HEV and BEV cases show higher additional consumption benefits compared to the conventional vehicle, probably due to improved regenerative braking.

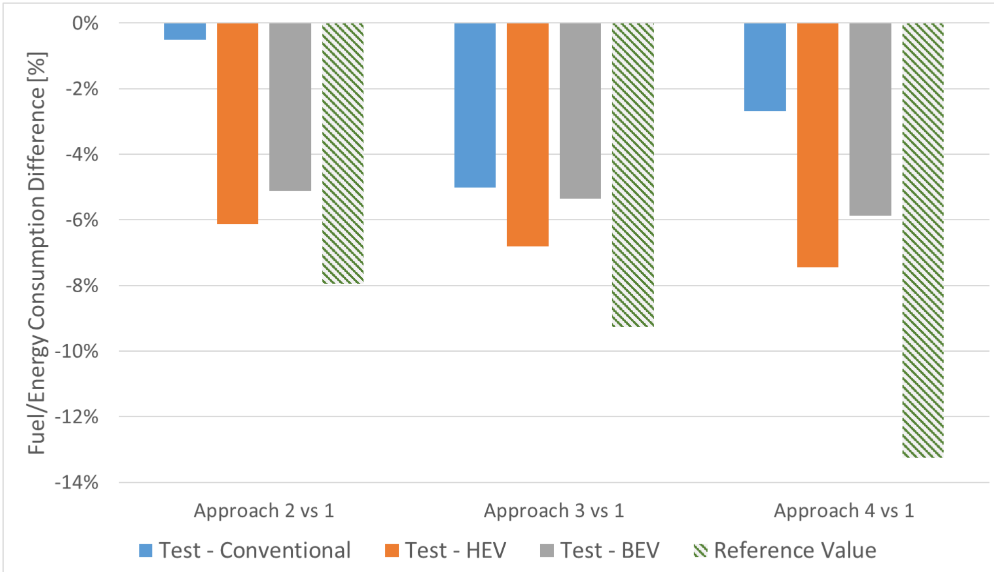


Figure 3-16. Summary of the relative fuel and energy consumption benefit for approach strategies 2 through 4 for Scenario 1 (patterning denotes reference values).

Scenario 2 represents approaching an intersection where a full stop is necessary, and the approach distance is long (long red light), such that there is sufficient time to create an optimized decelerating trajectory. For this scenario, a strategy for "coasting," such that the vehicle just reaches the intersection and nearly comes to a stop without the need to apply the brakes until the last moment was evaluated for its fuel consumption performance, compared to simply cruising through the intersection at a constant speed (as close to the "cruise" condition as possible).[58] As before, experimental results are provided for the different powertrain types evaluated as well as a comparison to the reference value.

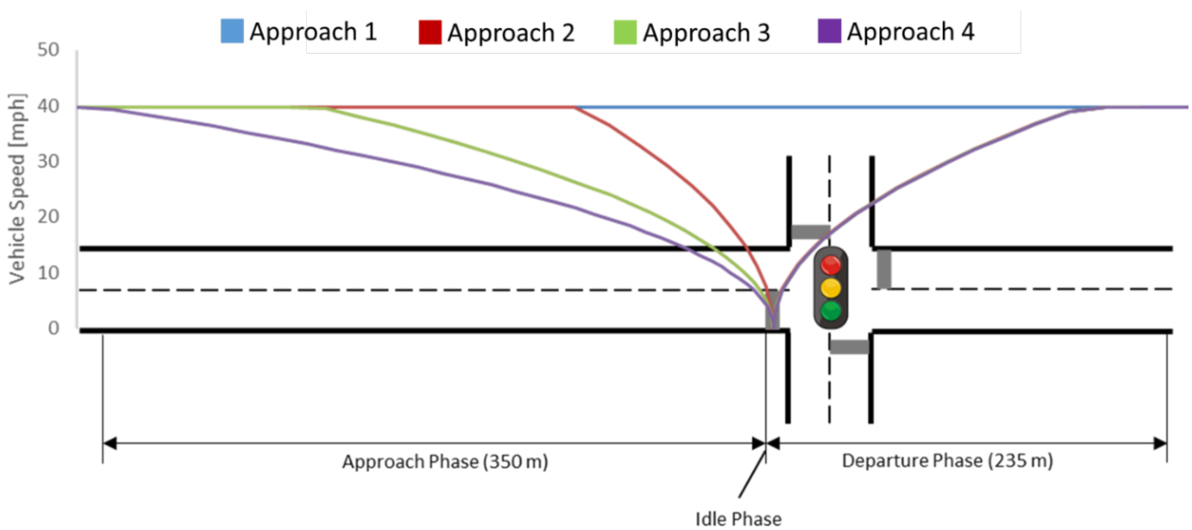


Figure 3-17. Intersection eco-approach with stop and idle required (Scenario 2).

Figure 3-18 summarizes consumption performance of the deceleration-based EAD strategies compared to simply cruising through the intersection (Approach 1) for all four powertrain types, plus the reference results from the original simulation-based paper. When comparing relative consumption for a vehicle coming to a complete stop at an intersection to one passing through on a green light, electrified vehicles, with their much lower consumption penalty associated with stopping and re-accelerating, have a significant advantage over a conventional vehicle. Even with idle stop-start technology and eco-driving approach strategies, the non-electrified vehicle tested for this study used more than double the amount of fuel when coming to a complete stop and accelerating back up to cruise speed than when cruising through the intersection. In contrast, the electrified vehicles (HEV and BEV) used at most 36% more energy in the worst case of coming to a stop rather than passing through the intersection. When compared to the results from the reference study used to create the experimental approach strategies, similar conventional vehicle results were observed, but the dramatically reduced consumption impact for stopping was not discussed for electrified vehicles.

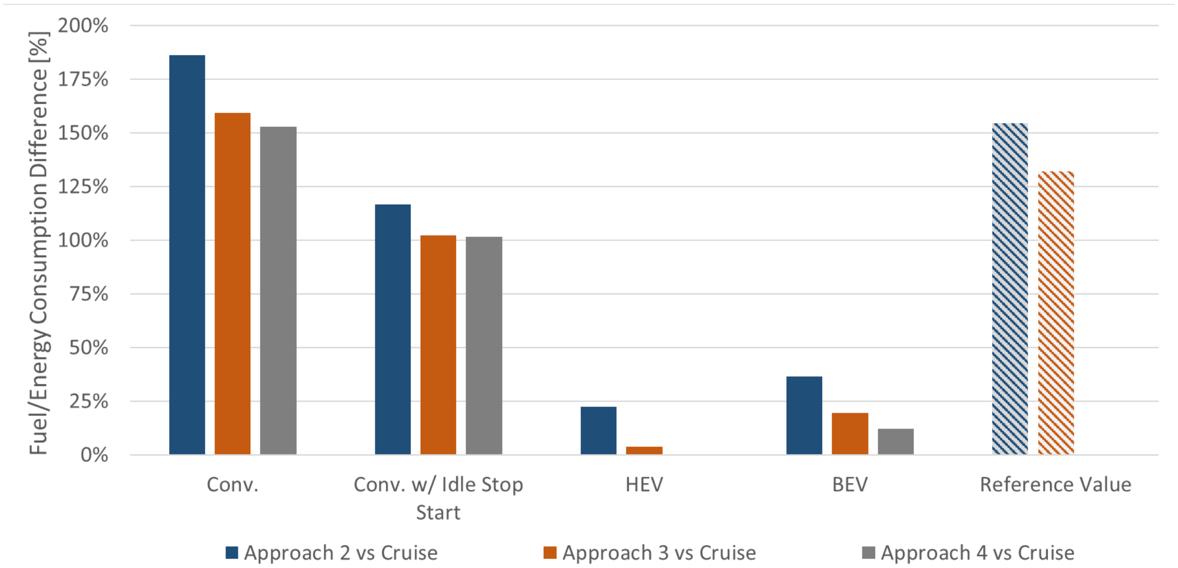


Figure 3-18. Summary of the fuel and energy consumption of approach strategies 2 through 4 for Scenario 2 compared to cruising (approach 1) through the intersection without stopping for Scenario 2 (patterning denotes reference values).

This experimental study evaluated the potential consumption benefits and sensitivities of key eco-approach and launch strategies for two different scenarios and four different powertrain types. The results showed that HEV and BEV powertrains could have higher energy consumption benefits from certain eco-driving strategies than conventional vehicles. Since many future CAVs are likely to be built on HEV or BEV platforms, these experimental results show the importance of applying eco-driving strategies to future CAV applications. Furthermore, while the reference results for conventional vehicles are relatively in-line with the experimentally observed benefits for conventional vehicles, the benefits and sensitivities of EAD strategies diverge significantly for electrified vehicles, thus warranting more study of powertrain-specific EAD strategies and approaches.

3.1.5.3 Field Evaluation of Eco Approach and Departure in Real-World Traffic Conditions

- The data collected in EAD field testing showed a moderate fuel savings of 10% to 20% compared with adjacent vehicles without EAD operating in an 80m zone centered at a controlled intersection (i.e., 40m before, 40m after). However, in this field testing, the frequency of encountering EAD scenarios was low, making the overall benefits at the trip level insignificant.

The benefits of EAD may be achieved in a number of ways when a vehicle travels toward an intersection as the traffic signal switches from green to red or vice-versa. When approaching a red signal, upon receiving the advisory information about the end of a red phase, a driver may slow down in anticipation of the signal phase change and pass through the intersection after the signal changes from red to green without making a full stop (as in Scenario 1 from the previous section). At the end of a green signal phase, to achieve fuel savings, the advisory information may cause an approaching vehicle to slow down earlier and with gentler deceleration than a vehicle without advisory information (as in Scenario 2 from the previous section), or to glide through before the signal switches to red (as in Scenario 1 and the cruise strategy in Scenario 2 above).

Under the SMART Mobility consortium, an EAD advisory application was field evaluated to understand the behavior differences between the test vehicles using EAD strategies and the surrounding vehicles within a corridor. The EnLighten mobile EAD app, from Connected Signals[59], was used to provide the state of approaching traffic signals to eco-equipped vehicles, including a red phase countdown and a "make/miss" speed range based on the future state of the signals ahead. For testing purposes, Connected Signals made modifications to its commercial version of its EnLighten software to also provide green phase countdown information. The red phase countdown enables EAD (similar to Scenario 1), while the green phase countdown facilitates both EAD (Scenario 1) and eco-approach (Scenario 2). EnLighten uses GPS data from cell phones to gather the location of the experimental vehicles and extracts the speed information.

Figure 3-19 shows the interface of the commercial EnLighten app. The arrows show the status of the signal in the direction of travel and change color to correspond with the actual signal phase. A countdown number replaces the arrow when the vehicle approaches an intersection. The emulated speedometer panel includes a numerical speed reading (e.g., the 20 in Figure 3-19 shows that the vehicle is traveling at 20mph) and a color band showing the advisory speed range in green. If the driver reduces speed such that it is in the red speed range, the vehicle may encounter a red light at the intersection ahead (i.e., the now green signal will have turned red).

Figure 3-19. EnLighten EAD software interface.

For this experiment, a corridor was instrumented with strategically placed video recording equipment to capture vehicle movement and documentation of traffic signal phase and timing information. Eco-equipped vehicles were driven by test drivers within the test corridor following the advisory EAD information. Image processing tools were installed to record the movement trajectories of the test vehicles, as well as the surrounding traffic, which enabled location and speed data to be derived for all vehicles at 0.1 second intervals of time.

A subsection of Santa Clara Ave. in San Jose, CA (shown in Figure 3-20), was the corridor used for data collection. This test corridor includes 10 intersections and nine road links, with an average distance between intersections of 82 meters. High resolution cameras were used to capture the environment, vehicles, and pedestrians within the corridor. Six of the cameras provided a "bird's-eye" view from the rooftops of surrounding buildings and two sets of cameras provided a street-level view where roof-top access was not possible.

Figure 3-20. San Jose eco-driving corridor overview and camera locations.

Figure 3-21 shows examples of the captured images. Advanced image processing techniques were used to process the captured video data to extract vehicle trajectories. Vehicle speed was then processed through a Kalman filter.

Figure 3-21. Example corridor video images (left bird's eye view, right: street view).

Five mid-size ICE sedans were used as the experimental vehicles. All vehicles recorded their respective GPS position, and each had unique markings so it could be easily identified in the camera images. One of the experimental vehicles also had an on-vehicle 360-degree camera, roof-top mounted LIDAR, and a high-precision GPS/INS position measurement system. The experimental fleet was then driven across a range of times of day and traffic scenarios over two consecutive weekdays.

Analyses conducted on the trajectory data enabled a direct comparison of the driving behaviors and fuel consumption of the test vehicles instrumented with the EAD function (eco-equipped) to their neighboring unequipped vehicles in the same traffic stream. The with/without comparison approach is an objective evaluation, as the vehicles with and without eco-driving are evaluated in the same environment, under identical traffic conditions, and with drivers in the unequipped vehicles being unaware of the test and behaving as they naturally would. In comparison, the before-and-after evaluation approach, typically used in earlier evaluations of eco-driving strategies can be significantly influenced by variations in testing conditions and the ability to collect adequate data for statistically sound analyses.

Fuel consumption was derived from the speed trajectory of each vehicle using the VT-Micro fuel consumption model for a conventional vehicle.[60] In this test corridor, the deceleration and acceleration of most of the vehicles occur from 40 meters before the stop line to 40 meters after the stop line. The driving behaviors and resulting fuel consumption for eco-approach (EA) related results was evaluated in the 40-meter range before the stop line, and EAD was evaluated by comparing various speed trajectories within the 80-meter range centered at the test intersection. The fuel saving benefits of EA and EAD scenarios are illustrated in the following case examples. Note that the actual fuel saving benefits for these scenarios may vary depending on the type of driver, model of vehicle, intersection setting, and control.

Figure 3-22 shows an example of eco-approach in which a vehicle is approaching an intersection when the signal switches from green to red and a full stop is necessary. The eco-equipped vehicle and unequipped vehicle travel in parallel in adjacent lanes when the signal switches from green to red. In comparison with the unequipped vehicle (green line), the eco-equipped vehicle (orange line) applied earlier deceleration to come smoothly to a stop. This case example shows eco-approach advisory information can facilitate earlier and smoother deceleration, which in turn leads to quantifiable fuel saving benefits. For this example, from the observed speed trajectories, the equipped vehicle achieved a fuel savings of nearly 9% over the unequipped vehicle in the 40 m approach zone.

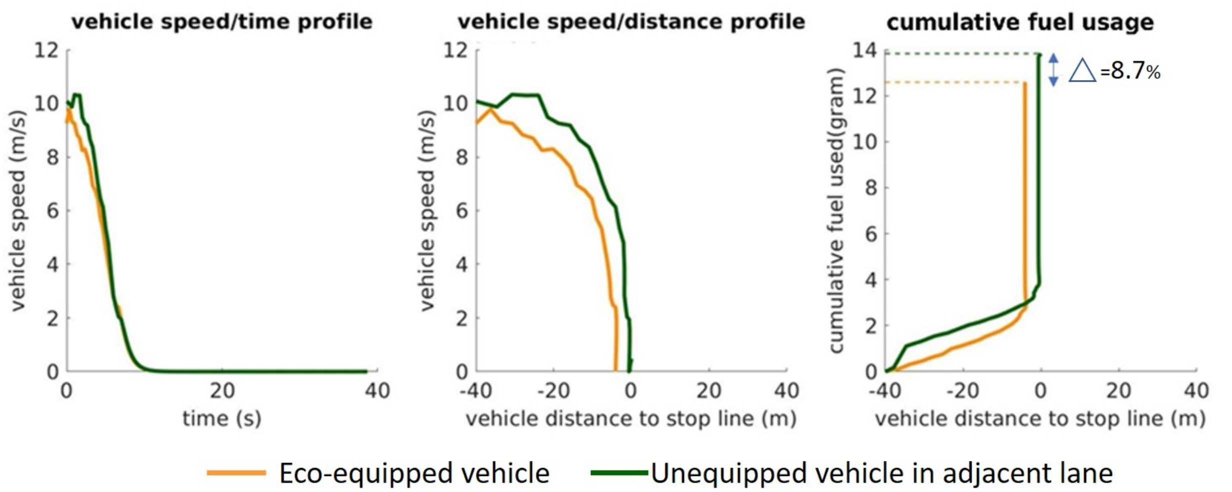


Figure 3-22. EAD Scenario 2: Eco-equipped and unequipped vehicles travel in adjacent lanes and arrive at intersection at a similar time.

Figure 3-23 presents a different example of eco-approach, in which an unequipped vehicle follows the instrumented vehicle in the same lane. The orange line represents the eco-equipped vehicle, and the blue line is the unequipped vehicle. In this example, the driver of the eco-equipped vehicle may have initially reacted to the green light countdown by accelerating, with the intention of passing through the intersection on the green, but then decided they would not be able to and slowed down to come to a stop (still using information provided by the EA device). As the lead eco-equipped vehicle (orange line) performs this deceleration, the trailing unequipped vehicle (blue line) decelerates in response to the leading eco-equipped vehicle. In this particular case, there was not an adjacent vehicle with which to compare. However, test data show that the fuel usage of the eco-equipped vehicle is less than the average fuel usage for unequipped vehicles in general. Most important, the trailing unequipped vehicle achieved more fuel saving than the leading eco-equipped vehicle (about 10% fuel saving for this example). This may be due to the fact that the eco-equipped vehicle initially accelerated and then utilized an EA strategy. This case illustrates how even an unequipped vehicle may gain fuel saving benefits when following an eco-equipped vehicle.

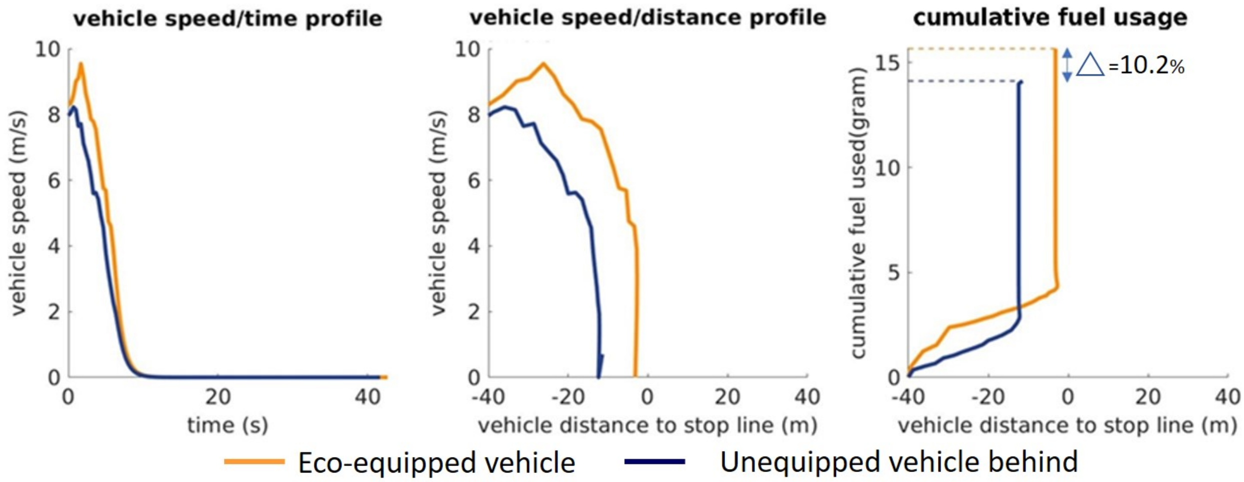


Figure 3-23. EAD Scenario 2: An unequipped vehicle follows an eco-equipped vehicle.

Figure 3-24 shows an example of EAD, in which vehicles are approaching a signal nearing the end of the red phase. The eco-equipped vehicle is further from the stop line than the unequipped vehicle and traveling in a parallel lane. With advisory information and sufficient lead time, the eco-equipped vehicle (orange line) decelerates then accelerates to avoid a full stop, while the unequipped vehicle (blue line) nearly comes to a full stop and then accelerates to pass through the intersection. This case example shows that EAD advisory information can help a driver to avoid a full stop as the vehicle approaches an intersection when the signal is switching from red to green, which in turn saves fuel (nearly 10%, in the 80m control zone in this example). However, this scenario is rather rare. Among the 82 passes of eco-equipped vehicles in this field study, only two additional Scenario 1 cases were observed, and these cases are without adjacent unequipped vehicles for comparison.

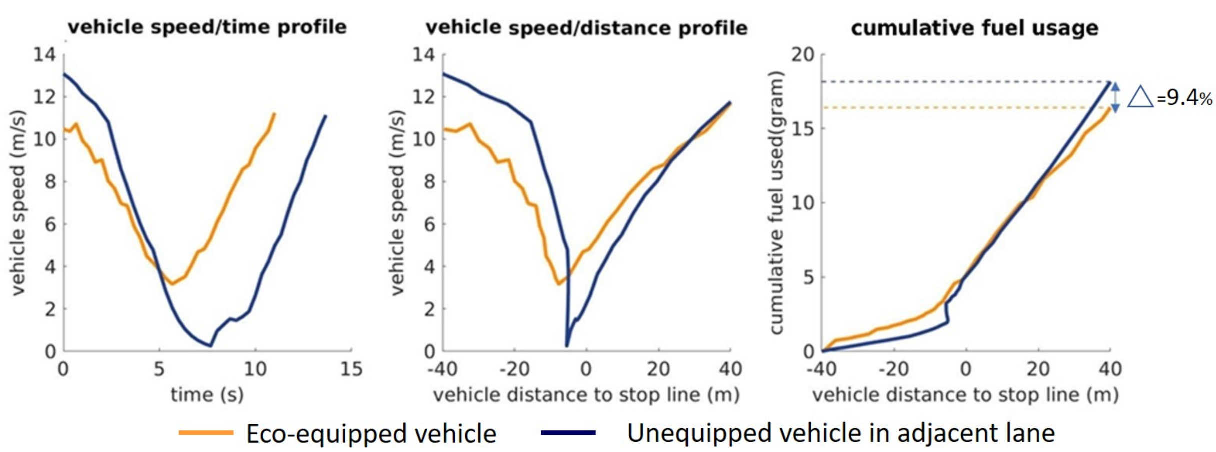


Figure 3-24. Case of Scenario 1: EAD Case I: An eco-equipped vehicle slows down but does not make a full stop. Unequipped vehicle in adjacent lane makes nearly a full stop

Table 3-1 summarizes the observed occurrences of traffic scenarios and estimated fuel consumption of all southbound vehicles at test intersection 5 in Figure 3-20 (Santa Clara St. and 4th St. in San Jose). During a cumulative 10-hour time window, 5,296 vehicles were observed passing through the intersection, with 82 eco-equipped vehicle arrivals. The data show that, in comparison with the vehicles without EAD information, EAD advisory information produced an average fuel savings of 3.5 grams or 13% per occurrence for vehicles approaching the test intersection at the end of a green phase (EAD Scenario 2), and an average fuel savings of

5 grams or 20% per occurrence for vehicles arriving at the test intersection at the end of a red phase (EAD Scenario 1).

Table 3-1. Eco-equipped vehicle fuel consumption (in 10 hours).

		# of occurrence s	% of Arrivals for EAD Vehicles	Average fuel consumed per occurrence (grams)	Cumulative Fuel Consumed (grams)	Average Fuel Saving due to EAD (grams)
All Vehicles	Cruise	2549		16.6	42313	
	Stopped	2747		26.3	72246	
Vehicles w/EAD	Arrive during green phase	52	63.4%			
	Arrive during red phase	17	20.7%			
	Arrive at end of red phase (EAD Scenario 1)	3	3.7%	21.3	63.9	15
	Pass at end of green (EAD Scenario 2 cruise)	0	0%			
	Arrive at end of green (EAD Scenario 2 Approach 2-4)	10	12.2%	22.8	228	35

While the fuel saving benefit per occurrence is considerable, the statistics from the experimental study show that the observed frequency of EAD scenarios is generally low at the penetration levels evaluated for this study. Among the total of 82 arrivals by vehicles with EAD at the test intersection within a 10-hour time period, EAD strategies were only applicable to about 15% of the cases, and did not offer any benefits for the remaining cases. Overall, 80% of observed cases were arrivals occurring during either the green phase or the red phase when EAD information was not helpful. More specifically, EAD enabled 3.7% of arriving vehicles to pass through the intersection without stopping at the end of red phase and 12.2% of vehicles to arrive with earlier and gentler deceleration leading to a stop at the end of the green phase. Interestingly, none of the eco-equipped vehicles were observed to increase speed in order to cruise through an intersection, most likely because the drivers were advised to observe speed limits and to not speed up to beat a red light. In real world consumer deployments, applications such as EnLighten do not typically provide a countdown for a green phase completion so that drivers are not led to run red traffic lights if the phase change were to be incorrectly predicted. To put the observed EAD occurrences in context, for a typical trip with an average trip length of 7 to 13 miles for various trip purposes and involving 10 signalized intersections, an eco-equipped vehicle may benefit from EAD advisory information at one to two intersections, resulting in a savings of less than 1% of the fuel consumed for the trip. Thus, the low frequency of encountering the EAD scenarios makes the overall fuel saving benefit due to EAD small at the trip level, based on this study's specific intersection configurations and the penetration implied by the amount of eco-equipped vehicles in the study.

However, it is worth noting that the number of vehicles benefitting from the EAD system may be greater than the total number of eco-equipped vehicles, as indirect benefits may be achieved for vehicles following eco-equipped vehicles (as in the example above). Also, note that the fuel saving results only represent an order-of-magnitude analysis. The actual fuel savings for EAD at both the trip level and intersection level can vary, depending on many factors, including the traffic control strategies, traffic conditions, and the way drivers use the EAD advisory information, as well as the types of powertrains operating within the system. Analyses also show that the distance between intersections can be an influencing factor. The fuel savings identified at the San Jose test site may be constrained due to the shorter distance between intersections (average 82 meters). EAD may become somewhat more effective when the distance between intersections is longer, so that drivers can take earlier actions to slow down for more fuel saving. Nevertheless, the field evaluation study concluded that the overall fuel saving benefit of EAD appears small at the trip level due to limited vehicle arrivals during a time-period where an EAD strategy would provide benefits.

3.1.5.4 Evaluation of Unproductive Fuel Consumption at the Signalized Intersection Level

- Field data gathered during EAD intersection testing for a specific intersection, showed that more than 80% of the time, vehicles stopping at that intersection did not encounter other vehicles at the conflicting approach. These unnecessary stops are the primary cause of unproductive fuel consumption at signalized intersections and accounted for over 15% of the total estimated fuel consumption at the test intersection. This suggests that, for the intersection assessed, more intelligent signal operation supported by connected vehicle and connected infrastructure technologies could lead to reduced stops and reduced fuel consumption.

When evaluating fuel saving benefits at the intersection level, it is critical to determine the level of unproductive fuel consumption that can be addressed by more situationally aware signal phase and timing. The unproductive fuel consumption for signalized intersections is defined as the excessive fuel consumption for vehicles being stopped by traffic controls when neither vehicles nor pedestrian activities are present at the conflicting approaches. While EAD may address a portion of unproductive fuel consumption when the signal is switched from green to red or vice versa, the unproductive fuel consumed when vehicles are stopped without the presence of any conflicting traffic should also be assessed.

An analysis of traffic behaviors and unproductive fuel consumption was conducted using the data collected at test intersection 5 (Santa Clara St. and 4th St., in San Jose). Table 3-2 summarizes the vehicle arrival rate and the potential fuel consumption of southbound vehicles approaching the test intersection. The data shows that among the roughly 52% of the vehicles stopping at the intersection, only 26% of the vehicle stops were at the same time as other vehicles were at the conflicting approaches (13% of total approaches). The remaining 74% of vehicle stops observed in the evaluation period involved no conflicting vehicles during the red phase (39% of total approaches), resulting in added fuel consumption for unproductive stopping and idling. The analysis revealed that unproductive fuel consumption due to unnecessary stops accounted for up to 30% of total fuel consumption at the test intersection. The analysis of unproductive fuel consumption only provides an order-of-magnitude estimate specific to the traffic conditions encountered and infrastructure capabilities assessed, yet this analysis reveals that unproductive fuel consumption at intersections is primarily attributed to unnecessary stops when no conflicting traffic or pedestrians are present.

Table 3-2. Vehicle stopping and fuel consumption at signalized intersection on August 7, 2019.

Event		Number and Percentages of Arrivals						Average fuel consumption		Unproductive Fuel Consumption per hour (gram/gallon)
		07:30 -08:30	08:30 -09:30	09:30 -10:30	10:30 -11:30	11:30 -12:30	12:30 -13:30	Per arrival (gram)	hourly average (gallon)	
Arrival at red phase	Conflicting vehicles present	25 7.0%	33 7.2%	61 12.8%	75 14.5%	103 14.5%	51 19.2%	28.7	0.51	0/0
	No conflicting vehicles present	172 48.5%	220 48.0%	150 31.5%	177 34.2%	224 41.8%	72 24.7%	25.1	1.31	1437/0.45
Arrival at green phase (passing through)		157 44.4%	205 44.7%	265 55.6%	265 47.8%	208 38.9%	168 57.7%	16.6	1.08	0/0
Total number of arrivals		354	458	476	517	535	291			

Analysis done within this report shows that unnecessary stops can be caused by inefficient traffic control at intersections, likely rooted in the suboptimal detection of approaching vehicles at intersections due to limited information provided by inductive-loop detectors, resulting in the traffic control not being able to adapt to the larger real-time traffic conditions. The unproductive fuel consumption at signalized intersections due to unnecessary stops cannot be directly addressed by EAD functionality. Rather, unproductive fuel consumption can be mitigated by advanced detection of vehicles by radar and/or cameras at intersections or with connected vehicle technologies that enable vehicles to communicate with intersections prior to their arrival. EAD can, when integrated with Connected Vehicle supported traffic control systems, offer added fuel saving benefits.

3.1.5.5 Unproductive Fuel Consumption at Stop-Sign Controlled Intersections

- For the stop-sign controlled intersection assessed for this work, the majority of vehicles arrived at the intersection without encountering a vehicle at the conflicting approach (68% at the test intersection), suggesting that additional benefits could be achieved with improved coordination via the reduced need for stopping.

Our analysis also assessed the driving behaviors and unproductive fuel consumption at a four-way stop-sign controlled unsignalized intersection in Pleasant Hill, California. The unproductive fuel consumption for unsignalized intersections is defined as the portion of fuel consumed by vehicles making decelerations and stops at intersections when no vehicles nor pedestrian activities are present at the conflicting approaches. At the unsignalzed test intersection, 360° cameras were installed on top of two traffic signs, and image processing techniques were used to process the captured video data and extract vehicle trajectories. Figure 3-25 shows the top view of the intersection where video data were collected. The red lines mark the stop line, the green points mark the driving vehicles, the red points are stopping vehicles, and the yellow points are conflicting vehicles. For example, in the scenario shown, the red vehicles 203529 and 203527 are stopping at the west stop line. The green vehicle 118 is driving inside the intersection. The yellow vehicle 100048 is approaching the intersection and is a conflicting vehicle for the stopping vehicles 203529 and 203527.

Figure 3-25. Unsignalized intersection in Pleasant Hill with mapped vehicle detections.

As with the signalized intersection data, speed profiles were extracted from the data to analyze vehicle behaviors before and after the stop line. Figure 3-26 shows the vehicle speeds as a function of distance to the stop line. Although all the vehicles decreased their speeds when approaching the stop line (dashed line), only a portion of the vehicles made complete stops (blue lines) as required by the traffic laws. A significant portion of the vehicles did not come to a full stop.

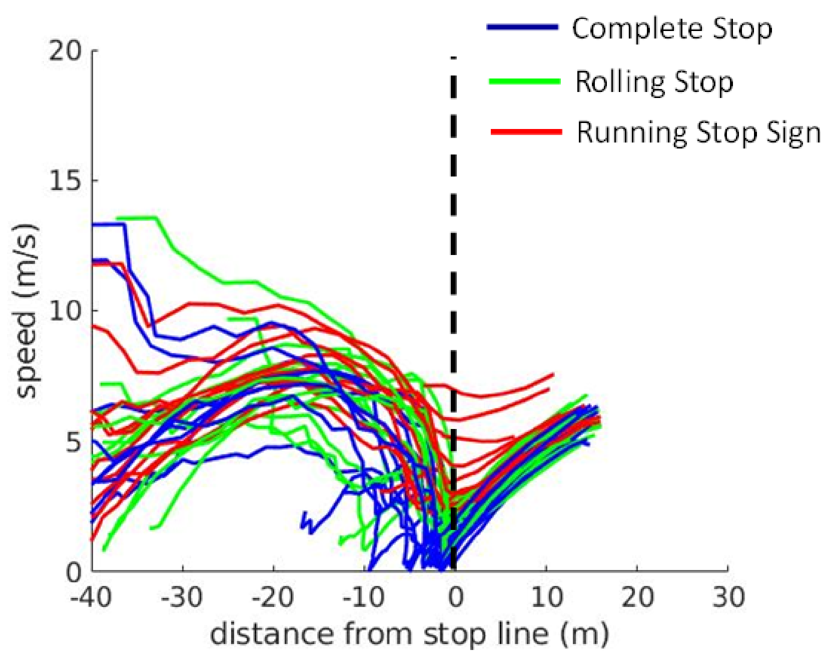


Figure 3-26. Speed profile of the vehicles. Dashed line marks location of the stop sign.

Table 3-3 summarizes the data collected for a weekday between 13:30 and 16:30 at the Peasant Hill stop sign controlled intersection. Analyses were conducted to classify the vehicle behaviors into complete stop (speed less than 1 mph), rolling stops (speed between 1 and 5 mph) and running stop signs (speed over 5 mph). The data show that 73% of the arriving vehicles from all approaches at this intersection did not make a complete stop, and 27% of all the vehicles made a full stop. Of the vehicles that made a full stop, 66% made full stops when there were vehicles at the conflicting approaches (18% of total approaches), while roughly 34% of vehicles made full stops when no vehicles appeared at other approaches (9% of total approaches). Further analysis shows that the rate of rolling stops and stop sign running has an inverse relationship to the rate of conflicting vehicles. Specific to this intersection, vehicles arriving from the east and west approaches had higher rolling stop and stop sign running rates, since the rate of conflicting vehicles from South and North approaches were lower. The analysis suggests that a portion of the full stops made at the stop lines were required by the presence of conflicting vehicles, i.e., not fully stopping was not an option. The unnecessary stops result in travel delays and unproductive fuel consumption. Though stop signs are perceived as promoting traffic safety, improper use of stop signs can cause many drivers to ignore them, creating a more hazardous situation.[61]

In order to estimate unproductive fuel consumption, the trajectory of slow-down-then-speed-up activity of each vehicle within the range of 40m before and after the stop sign was fed into the fuel consumption model. When there are no conflicting vehicles, if the vehicle makes a stop or slows down, the extra fuel is uses (unproductive fuel consumed) is compared with a reference vehicle that keeps a steady speed to cross the intersection. The unproductive fuel consumption for the observation period reaches 1.0 gallon/hour at the testing intersection, accounting for over 30% of the fuel consumed at this intersection. The analysis also indicates that the unproductive fuel consumption at an unsignalized intersection, within the range of 40 m before and after the stop sign, can be as high as 60% of the fuel consumed at that intersection (within the assessment zone) if all vehicles make proper full stops.

The unproductive fuel consumption at unsignalized intersections can be reduced if vehicles are allowed to pass through the intersection at a steady speed when no vehicles or pedestrians are present. Among potential remedies, signal control with intelligent vehicle and pedestrian detection can be an effective way of minimizing unproductive fuel consumption. However, most of the current unsignalized intersections do not have enough vehicular and pedestrian volumes or crash history to justify the installation of traffic signals as defined by the Manual on Uniform Traffic Control Devices.[62] Alternatively, yield signs are appropriate in some cases to call on drivers to slow down, defer to oncoming traffic, stop when necessary, and proceed when safe. Connected Vehicle technologies have the potential to offer more intelligent solutions to maintain safety and efficiency while reducing the unproductive fuel consumption at unsignalized intersections. Further work on innovative strategies/technologies is needed.

Table 3-3. Vehicle stopping and fuel consumption at unsignalized intersection (13:30 to 16:30).

	Event	Total # of arrivals/hour	Average fuel consumption per arrival (grams)	Average hourly fuel consumption (gallon)	Unproductive fuel consumption (gallon)
Full stop	With conflicting vehicles	151 17.56%	20.4	0.81	0
	Without conflicting vehicles	79 9.1%	17.6	0.36	0.21
Rolling vehicles	With conflicting vehicles	86 10.0 %	15.9	0.36	0
	Without conflicting vehicles	295 34.3 %	14.6	1.13	0.54
Running vehicles	With conflicting vehicles	41 4.7 %	13.4	0.14	0
	Without conflicting vehicles	208 24.19%	12.2	0.67	0.25
	Reference steady speed vehicle @ 22mph		7.6		
	Total	860			

3.1.5.6 *Summary*

The experimental studies conducted by the CAVs Pillar show that moderate levels of fuel consumption improvement may be achieved when a vehicle arrives at an intersection shortly before the signal is switched from green to red or from red to green and a driver responds to the EAD advisory information in a fuel-saving manner (this is called a "benefited arrival"). On the other hand, the experimental studies have shown that the chances of vehicles encountering end-of-the-green/red scenarios at intersections are generally low. Therefore, for an individual vehicle, the fuel saving achieved by EAD at the trip level is insignificant. The field studies also reveal that fuel savings due to EAD at the intersection level may become noticeable if the total number of "benefited arrivals" is high. However, high rates of EAD equipped vehicle benefited arrivals are difficult to achieve until the overall penetration of connected vehicles is high.

The analyses of the field data generated under SMART Mobility also indicates that additional investigations could focus on unproductive fuel consumption due to unnecessary controlled stops at both signalized and unsignalized intersections. During testing in the eco-equipped corridor described in this section, considerable unproductive fuel consumption occurred at intersections due to situations when vehicles stopped at intersections when no conflicting traffic was present. This work validates the promise of CAV technologies that can prevent vehicles from stopping unnecessarily when no conflicts are present, thus substantially reducing unproductive fuel consumption for both signalized and unsignalized intersections. Further studies are needed to develop specific CAV applications that can realize this potential at a larger scale and contribute to substantial fuel savings while improving safety at intersections.

3.1.6 Real-World Driving Data and Strategies for Green-Routing Applications

- The RouteE tool was developed to make pre-trip vehicle energy consumption estimates, and initial validation testing indicates that RouteE accurately identifies which will be the least energy consuming ("greenest") route among various alternatives.
- A large-scale green routing opportunity evaluation, leveraging data on 45,000 actual trips, found that a less energy consuming route alternative existed for about one-third of these trips, and that among this subset of trips with a fuel saving route alternative, the aggregate fuel consumption of the "greenest" routes was estimated to be 12% lower than that of the originally selected routes.
- Among the subset of routes with a less fuel consuming route alternative in the large-scale study, roughly half of the less fuel consuming routes also have a lower travel time. These "double win" cases account for roughly two-thirds of the fuel saving potential, with the other one-third requiring some level of travel time penalty to achieve the fuel savings.

Green routing tools select travel routes that minimize energy consumption and present an important fuel saving opportunity for CAV technologies. The CAVs Pillar developed, validated, and applied a methodology that considers the relationship between driving conditions (road type, grade, traffic, etc.) and energy consumption for a given vehicle. Accurately representing this relationship enables optimization and selection of routes that minimize energy consumption. (As described in Sections 3.1.4 and 3.3.5.2, other applications of this capability include estimating aggregate energy consumption for a specific vehicle or for all vehicles traveling on a given road, a city's entire road network, or even the national road network.) Through these efforts the methodology developed became formalized as the RouteE energy estimation tool. At its core, RouteE relies on detailed training data for a given vehicle model to establish the relationships between driving condition and vehicle energy consumption rate. These training data could come from comprehensive on-road physical data collection or be supplied by higher-fidelity vehicle model simulations over a comprehensive set of detailed real-world driving profiles (e.g., using a validated tool such as FASTSim[63] or Autonomie[64]). Additional background on RouteE can be found in the SMART Modeling Appendix. Beyond helping to formalize development of the tool, the CAVs Pillar conducted a focused validation effort on RouteE and applied RouteE to estimate the large-scale energy benefits of green routing.

The focused validation activity included collecting on-road fuel consumption data from identical pairs of conventional, hybrid, and plug-in hybrid electric vehicles driven along different routes between the same origins and destinations.[65] Figure 3-27 shows two of the routes from the data collection effort in Phoenix, Arizona — one traversing only surface streets and the other driving primarily on a controlled access highway. RouteE models were subsequently trained for each of the vehicle types. A variety of approaches can be employed for training RouteE models, including various machine learning techniques that have been successfully used in other applications. For this effort, training involved running large-scale simulations of FASTSim vehicle models over real-world data from the Transportation Secure Data Center (TSDC)[66], then binning the large-scale simulation results based on driving condition parameters (e.g., road grade, traffic speed, road type and orientation/turns taken). Averaging the many simulation results that coincide with each driving condition bin resulted in a multi-dimensional lookup table of representative fuel consumption rates for each driving condition. Following such training to establish a RouteE model for a given vehicle type, RouteE was then validated for its ability to accurately estimate relative energy consumption differences between the actual vehicles driving each route from the physical testing — including testing conducted at different times of day and thus in different traffic conditions.

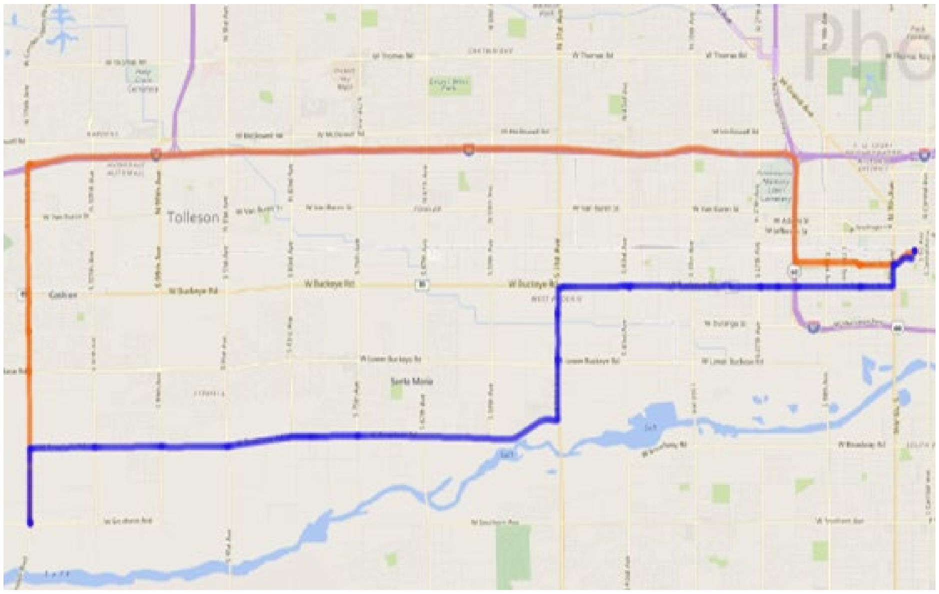
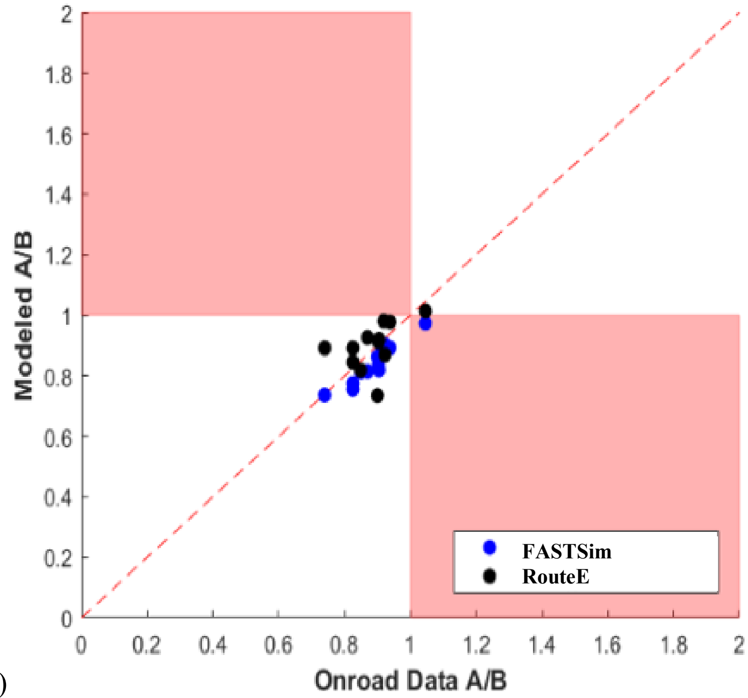


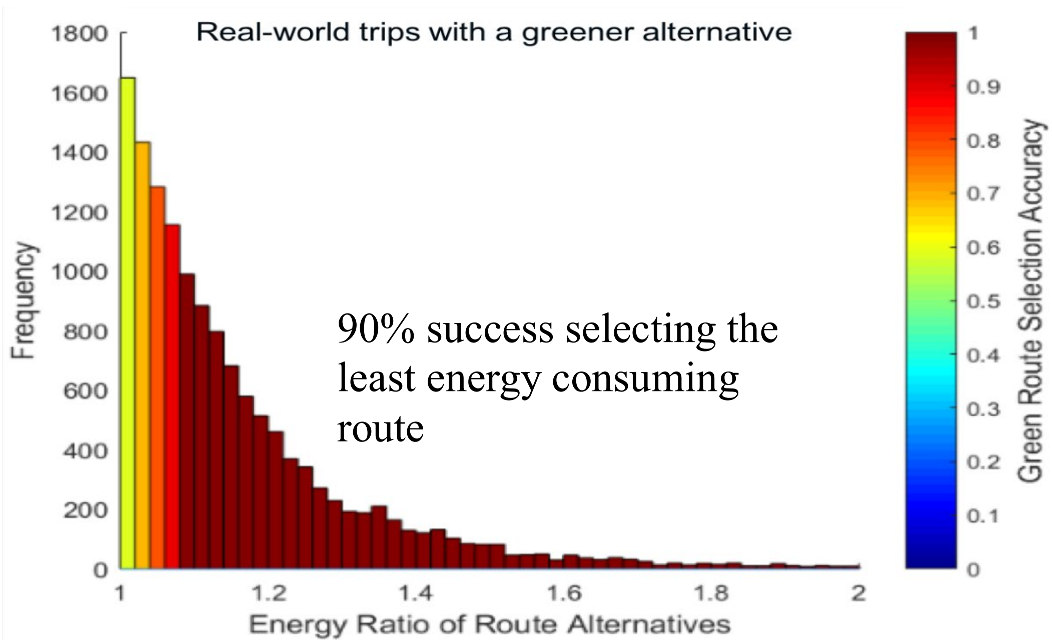
Figure 3-27. Two of the routes driven during on-road data collection in Phoenix, AZ.

The validation effort successfully demonstrated RouteE's ability to accurately predict which route alternative would be the "greenest" (i.e., consume the least amount of fuel). Figure 3-28(a) illustrates the findings for one of the evaluated vehicles over a dozen different on-road test scenarios. Each axis of the figure plots the ratio of energy consumed on the surface route (option A) over that consumed on the highway route (option B), with the x-axis indicating this ratio as calculated from the on-road test data and the y-axis indicating model estimates of this ratio. Note that the figure includes results for both a basic FASTSim model (making use of the actual second-by-second driving trajectories traversed by the test vehicles) as well as the RouteE estimation results (made without the benefit of the actual second-by-second driving profile as this would not be available in a true pre-trip application). Unsurprisingly, the RouteE estimates show greater scatter than those from the basic FASTSim model, but RouteE nevertheless demonstrated 100% accuracy for predicting which of these pairs of tested routes would be less energy consuming. Note also from this plot that the actual energy consumption differences between the measured route pairs varied from roughly no difference to over 20% difference.

Figure 3-28(b) examines how the model would be expected to perform over a much larger real-world dataset, given the 9.1% root-mean-square-error (RMSE) calculated for RouteE's ability to predict the relative energy consumption differences between the smaller set of tested route pairs. This assessment relied on an early version of the larger scale green routing impact analysis, where a subset (about 14,000 trips) of real-world data from the TSDC were used in combination with a routing application programming interface (API) to identify different routes between the real-world trip origins and destinations and to subsequently estimate which of the route options would require the least amount of energy to drive. For each trip, the larger amount of energy estimated for other viable route alternatives was divided by the energy required by the least energy consuming route option to calculate the set of route alternative energy ratios plotted in Figure 3-28(b) as a histogram. Applying a probability function (based on the RouteE RMSE testing result) to the large set of real-world trip data demonstrates an expected 90% success rate for RouteE to select the least energy-consuming route. Note that most trips within this large real-world sample show energy consumption differences between alternate routes in a range similar to that of the smaller scale instrumented vehicle tests, but there are also route alternatives in the larger set of real-world origin–destination pairs that show potential fuel savings even higher than 20%. This validation effort demonstrated that the novel energy estimation techniques deployed in RouteE are suitable for green routing applications.[67]



(a)



(b)

Figure 3-28. Green routing methodology assessment - (a) The plot highlights regions that indicate correct (white) and incorrect (red) selection of the least energy-consuming route option by the basic FASTSim (blue) and RouteE (black) models and (b) estimated success rate identifying the greenest route based on the RMSE from on-road validation of the RouteE model. The distribution demonstrates that the model will accurately select the least energy-consuming route for 90% of real-world trips.

The broader green-routing opportunity analysis utilized a larger-scale version of the TSDC trip data referenced in Figure 3-28(b) and compared time and energy differences for alternative route options compared to the actual route chosen by drivers. Specifically, matched origin–destination pairs from 45,000 trips in the TSDC were fed into a routing API (from Google Maps), along with the day of week and time of day that the actual route was driven. Based on this information, the API returned the most viable route options between each origin–destination pair (along with estimated travel times), and RouteE was used to estimate the required energy consumption for each of the route options. As the TSDC data included information on the actual route driven, these time and energy consumption estimates were made for the actual routes along with the top alternative routes between each origin–destination pair.[68,69]

The analysis found that for conventional vehicles a potentially less energy consuming route alternative existed for 31% of these actual routes. Among this subset of trips with a fuel saving route alternative, the aggregate fuel consumption of the "greenest" routes was estimated to be 12% lower than that of the originally selected routes. When considering the travel time impacts of these alternative energy saving routes, it was found that about half of them resulted in faster travel times as well as fuel savings, and the other half incurred some amount of travel time penalty. Figure 3-29 shows a scatter of the estimated energy savings and travel time impacts for the subset of real-world trips with energy savings potential. All points above the dashed horizontal line represent alternatives that present a time and energy savings (representing a "double win"), whereas those points below the horizontal line represent some degree of tradeoff between travel time and fuel savings. Among the points below the horizontal axis, those resulting in the steepest negative slopes relative to the origin (i.e., falling close to the negative vertical axis) represent the least favorable travel time to fuel savings tradeoffs. As line segments with increasingly less negative slopes sweep the region in the lower portion of the figure, the points where they intersect represent increasingly more favorable tradeoffs between travel time penalties and achievable fuel savings (with the most favorable options falling close to the horizontal axis). A promising finding in this combined assessment of fuel savings and travel time impacts is that those "double win" routes where both fuel and time savings occur account for two thirds of the overall energy savings — underscoring the substantive and potentially easy-to-achieve opportunity that green routing could provide for connectivity-enabled vehicle fuel savings.[70,71]

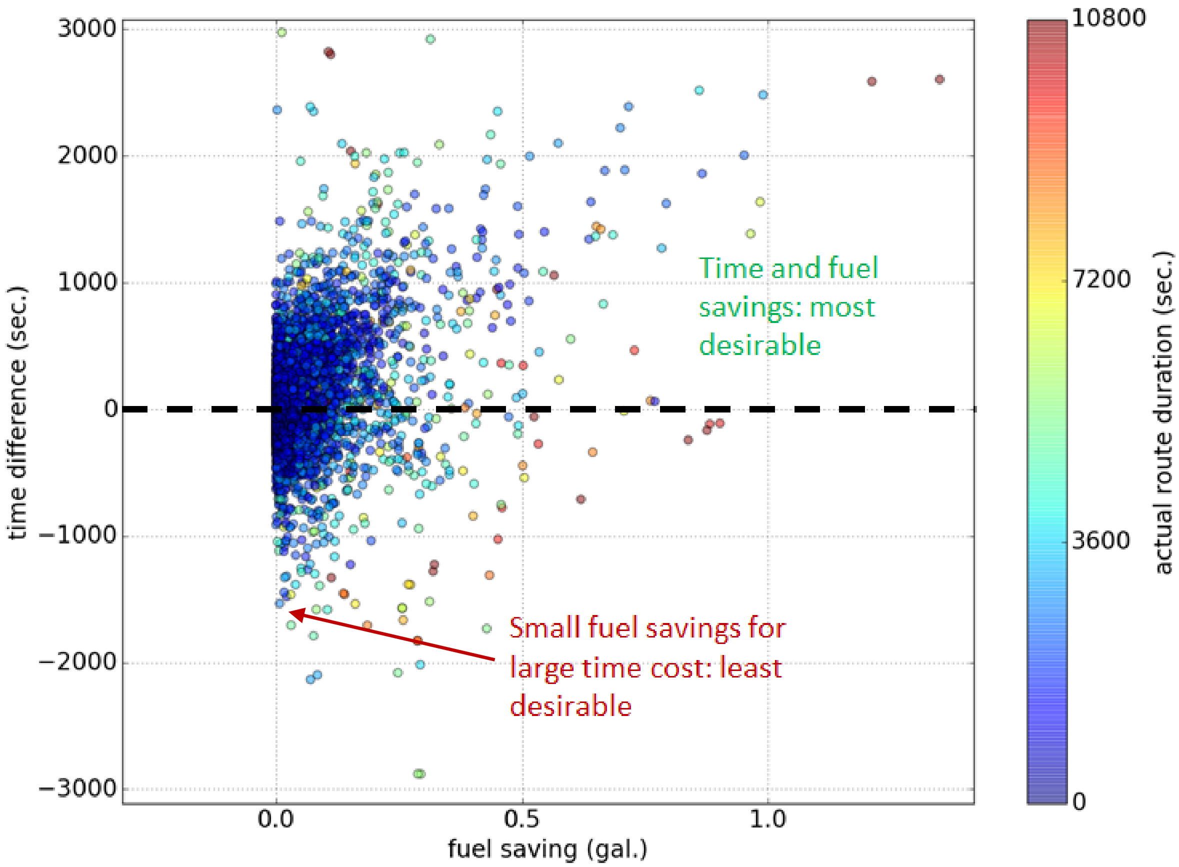


Figure 3-29. Energy savings vs. time savings for alternative routes compared to actual routes.

3.1.7 Accessory Loads and Sensitivities for Automated Vehicles

- Energy consumption sensitivity impacts of electrical loads vary significantly depending on cycle average power consumption and thus should be represented as an additional load applied to a cycle, not a percentage increase in consumption.
- Various electrical loads have been applied to MY2019 BEVs and ICEs to show sensitivities to automation system electrical load across a range of levels. For example, a 2000W additional load shows overall real-world increases in consumption ranging from 17% to 30% for BEVs and 6% to 24% for ICEs.
    - In contrast, if this load is applied over the UDDS cycle, the consumption increase is 38% to 70% for BEVs and 10% to 50% for ICEs.
- Field testing of a Cadillac CT6 with Super Cruise, a L2+ automation system, found automation system loads slightly above 100W when actuation, processing, and sensing loads are included.
    - The additional electrical loads changed minimally when Super Cruise was deactivated, suggesting that for lower-level automation capabilities, the true accessory load penalty for certain eco-behaviors may be minimal if these systems are already in use for safer driving.
- Field testing of an automated vehicle prototype, provided by an industrial project partner, found automation loads ranging between 300W and 400W for functionalities including hands-free highway operation (L3) and fully self-driving operation and navigation at lower speeds (L4). These electrical

load levels suggest that many automation functions may be implementable at loads lower than the 2-4 kW seen in recent driverless capable pilot fleets.

Vehicle automation, especially higher-level capabilities that require minimal input from the driver and allow for more efficient operation and coordination, have begun to show significant potential for decreased fuel/energy consumption. While the information, awareness, and capabilities attributed to these automation systems offer many potential strategies for efficient operation, the sensors, processing and actuation components required by these systems represent a new additional power load which can reduce or cancel out the benefits provided by these new eco-capabilities. As several highly automated vehicle pilot fleets have begun testing, issues regarding the power consumption associated with these systems have come to the forefront, as several of these pilot fleets have experienced individual vehicle power consumption on the order of 2kW to 4 kW, which represents a significant increase in overall vehicle energy consumption.[72,73] On the lower end of the spectrum, Tesla has recently announced its "Full Self Driving Chip" with a claimed 72 W power load[74], although it is unclear how many additional components are required to assess the total energy consumption of their automation system. Similarly, researchers have also begun to look into the expected additional electrical loads and subsequent impacts of these loads on vehicle efficiency and consumption.[75,76]

Despite this elevated interest, significant uncertainty remains regarding the expected loads for vehicle automation, particularly automation systems capable of driverless operation, with estimates varying widely from 240 W[77] to 3 kW[78][79] and beyond. Moreover, studies that address the consumption impacts of these additional loads tend to focus on a single vehicle per powertrain option, which is not always recommended since electrical load impacts vary significantly with overall vehicle efficiency and type. Additionally, the electrical loads associated with automation have often been treated as "one size fits all," with any automated driving capability attributed to a single electrical load. In practice, there is a spectrum of automation loads associated with the sensing and processing needs for a certain set of functionalities (i.e., more sensing and processing required for driverless operation versus basic hands-free driving). While automation systems are rapidly changing and evolving, this work created a snapshot of current vehicle and system trends while also providing insights applicable to future automated vehicle systems.

Given the importance of understanding the impact of automation system loads on overall vehicle operational efficiency, as well as the current uncertainty in the public and research literature regarding expected loads, this research refined and expanded on the current literature related to automation loads and their impacts using a mix of experimental vehicle testing, analysis, and on-road commercial and prototype system testing. More specifically, this work first sought to identify the consumption sensitivities of very recent (MY 2018-2019) vehicles to a range of additional electrical loads and consumption levels. The second component of this work was to evaluate the loads associated with several automation systems under real-world operating conditions by using on-road field testing of instrumented vehicles. While certainly not intended to be exhaustive, this work then builds upon these diverse sets of experimental data to identify the trends, insights, and conclusions related to loads associated with automation systems and their impacts on overall vehicle system efficiency.

3.1.7.1 Vehicle Electrical Load Sensitivity Analysis

- Energy consumption sensitivity impacts on electrical loads vary significantly depending on cycle average power consumption and thus should be represented as an additional load applied to a cycle, not a percentage increase in consumption.
- A range of electrical loads have been applied to MY2019 BEVs and ICEs to show sensitivities to automation system electrical load across a range of levels. For example, 2000W additional load shows overall real-world power consumption increases ranging from 17% to 30% for BEVs and 6% to 24% for ICEs.
    - In contrast, if this load is applied over the UDDS cycle, a consumption increase of 38% and 70% for BEVs and 10% to 50% for ICEs.

While several simulation-based studies have recently begun to investigate the impacts of various automation system electrical loads on overall system efficiency, these results often use vehicle models built upon earlier vehicle generations, which may not fully represent the efficiency and characteristics of today's current fleet of vehicles. For example, the EPA Label MPGe (a proxy for overall vehicle electrical efficiency) of a MY 2012 Nissan Leaf is roughly 20% lower than that of a MY2019 Chevrolet Bolt. Similarly, ICE-powered vehicles have also increased in efficiency compared with previous generations, so it also important to consider more recent ICE vehicles when investigating automation system load impacts. With this in mind, dynamometer testing of select recent vehicles was used as a baseline to which the additional automation system loads were applied. This testing was used as a preliminary validation point for specific load impacts as well as to define estimates for parameters relevant to understanding electrical load impacts across vehicles. Specific to this work, dynamometer based testing of a MY2019 Chevrolet Bolt was used as a starting point for BEVs and a MY2019 Toyota Camry was used for the ICE assessment.

To begin with the BEV case, Figure 3-30 summarizes the tested cycle-average DC energy consumption for the Bolt over U.S. regulatory cycles (secondary axis) and the subsequent estimated impact of a range of additional electrical loads applied during operation over these cycles (primary axis). Loads ranging from 250 W to 3000 W were selected in an attempt to cover the majority of cases discussed in recent literature, although loads of more than 3 kW have been reported for certain prototype vehicles.

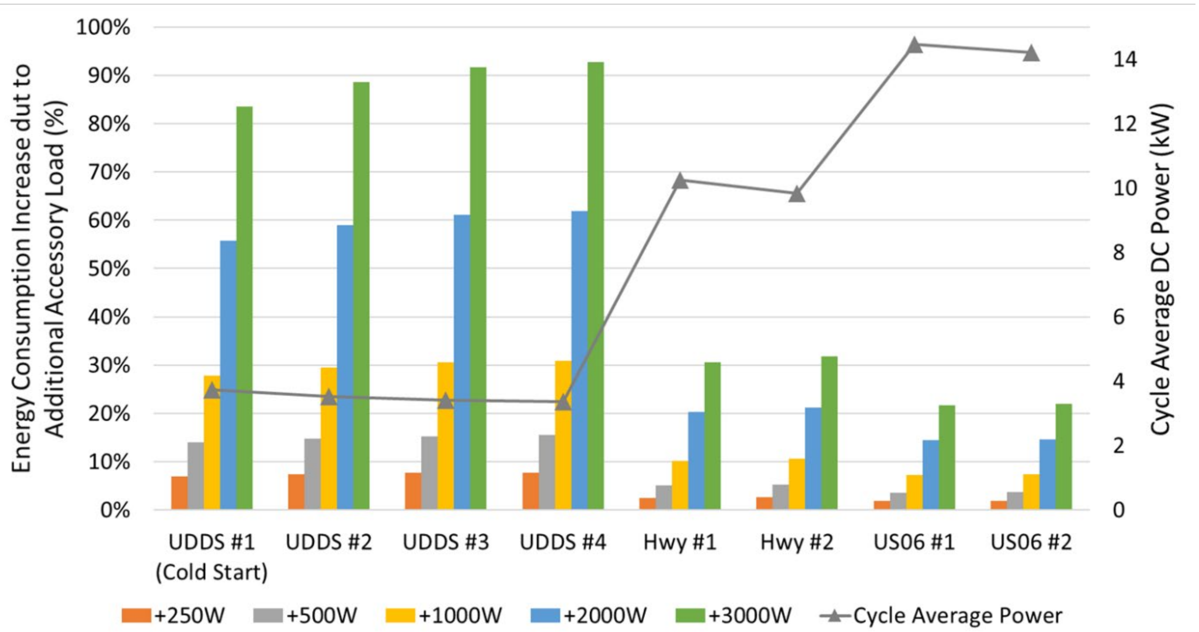


Figure 3-30. Chevrolet Bolt estimated additional load sensitivity and cycle average energy consumption for U.S. regulatory cycles.

The clearest observation from the Bolt testing is that the impact of additional electrical loads (for a BEV) is very strongly related to the average energy consumption of a particular drive-cycle. The Urban Dynamometer Driving Schedule (UDDS)[80], a relatively mild drive cycle, shows a significantly larger relative impact than the much more aggressive US06 Supplemental Federal Test Procedure (US06)[81]. For example, 2000 W of additional electrical load is estimated to have a 55%–62% overall consumption impact for UDDS driving, whereas the same load results in roughly a 14%–15% overall consumption increase for US06 driving. Even for back-to-back repeats of the same driving cycle (i.e., UDDS 1-4), the impact of the additional electrical load changes noticeably due to cycle-to-cycle warm-up and other variations. These results again highlight the observation from previous studies that automation system electrical load is an important consideration when evaluating overall vehicle energy consumption. Furthermore, when considering the impact of a particular automation system load, a simple percentage multiplier (i.e., 700 W = X% consumption increase) is likely to be misleading except in the aggregate case.

Building on the BEV sensitivities observed for the Bolt testing, the next step was to apply these insights for a range of recent BEVs. It stands to reason that the observed sensitivity to cycle average power will also be relevant when investigating BEVs with different weight and vehicle characteristics (efficiency, drag, rolling resistance). To accomplish this task, the same range of additional electrical loads were applied to all of the BEV results in the EPA MY2019 data repository[82], which collects consumption data over select U.S. regulatory cycles (UDDS, HWFET for BEVs). The estimated UDDS and Highway Fuel Economy Test (HWFET) consumption sensitivities due to additional electrical load for MY2019 BEVs are shown in Figure 3-31, with each individual entry on the X-axis corresponding to a distinct MY2019 BEV. These results again highlight the observation that UDDS and HWFET sensitivities differ significantly. In addition, a significant range of impacts due to the vehicles themselves can also be observed. For example, the impact of a 2000 W additional electrical load applied to all MY2019 BEVs varies between 38% and 70% for UDDS operation versus 15-26% for HWFET operation.

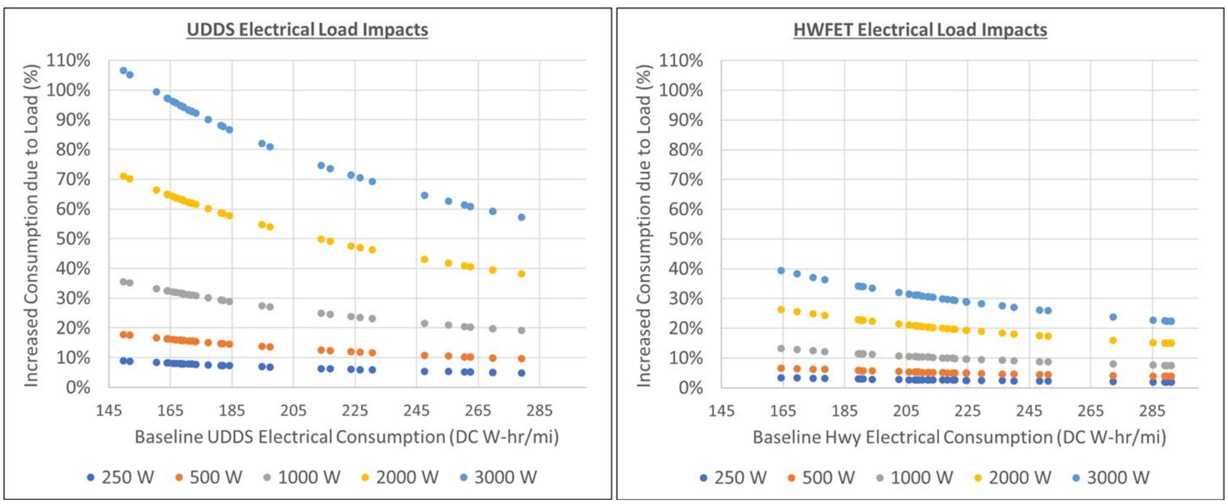


Figure 3-31. Baseline highway electrical consumption for MY 2019 BEVs and their estimated UDDS and HWFET energy consumption sensitivities.

While it is useful to observe the individual sensitivities for the UDDS and HWFET cycles to illustrate a range of possible impacts across automation system power levels, a combined estimate of real-world impact expectations is useful as well. As shown in Figure 3-32 below, the real-world adjustments detailed in 40 CFR § 600[83] were used to create an estimated real-world impact due to electrical loads applied to the same set of MY 2019 BEVs.

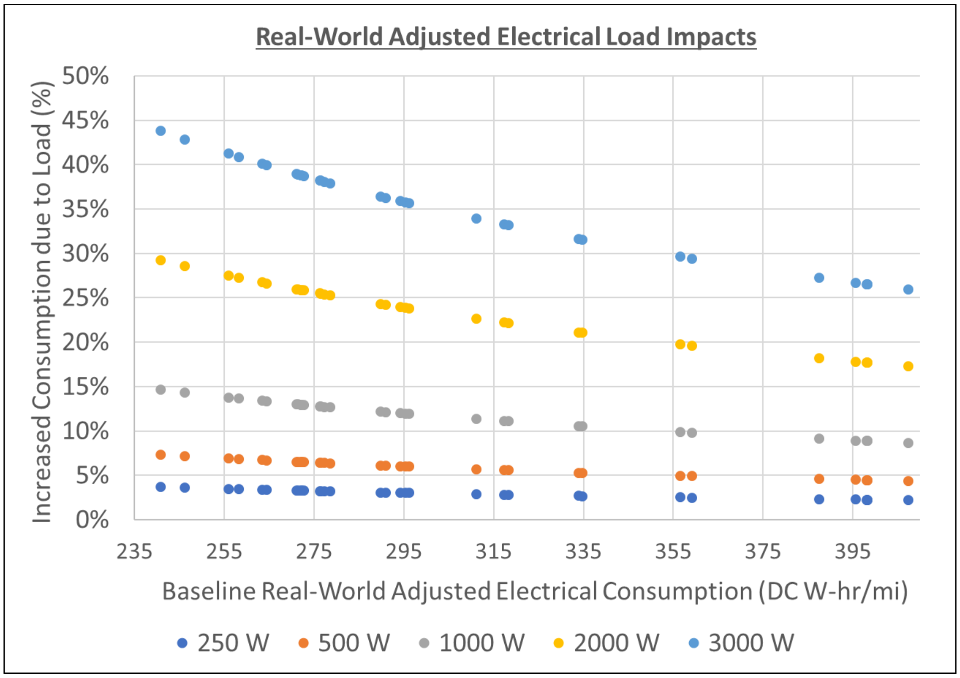


Figure 3-32. Estimated real-world consumption sensitivity to additional electrical loads for MY2019 BEVs.

As before, a significant range of sensitivities can be observed at each level of additional power due to the baseline performance of the vehicle to which the additional loads are applied, but the overall impacts are much more muted than the dramatically large impacts observed for the UDDS cycle. That said, even for real-world adjusted values, the additional loads due to a particular automation system will have a significant impact on overall BEV energy consumption and must be considered when estimating the benefits of a proposed AV operating strategy. Additionally, for BEVs these dramatic increases in energy consumption lead to significant decreases in vehicle range and thus must be intelligently considered when sizing components as well as defining trips that can be made without requiring a recharging session.

As in the BEV analysis above, experimental data for a recent ICE vehicle was used to provide baseline parameter estimates and sensitivity validation for an ICE vehicle. This information was then applied to a much larger set of MY2019 vehicles contained in the EPA Vehicle Database to estimate both cycle-specific and vehicle performance specific consumption sensitivities to additional electrical load. ICE fuel consumption increases due to additional electrical loads is also very dependent on both the drive cycle and an individual vehicle's baseline performance and characteristics. Overall consumption impacts are somewhat lower than those for BEVs, with a 2000 W additional load representing a roughly 10%–50% increase in consumption, compared to the BEV's 38%–70%. Interestingly, the spread of sensitivity (max%–min%) is much larger for MY2019 ICEs than for BEVs. This because MY2019 ICE vehicles include a range of economy cars to sports cars encompassing a very large set of fuel consumption values, while the range of BEV energy consumption for MY2019 vehicles is considerably smaller.

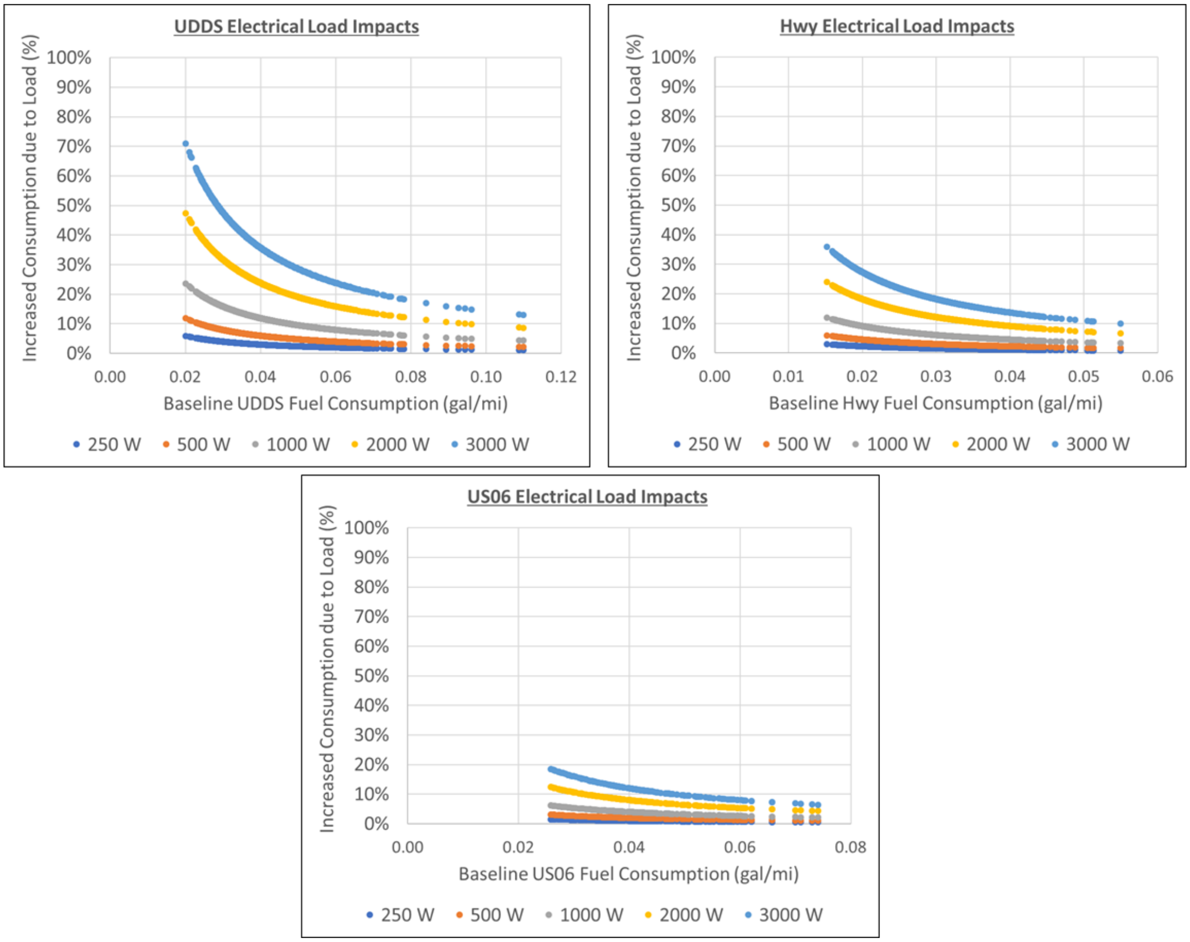


Figure 3-33. MY2019 ICE estimate electrical load sensitivity for UDDS, HWFET, and US06 cycles.

An aggregate estimate for real-world sensitivities to additional electrical loads was created for the ICE MY2019 results. As expected, the overall impacts are more muted than the much larger impacts estimated for the UDDS cycle in the above analysis, and a very large range of impacts for a given load level was estimated because of the wide variations in MY2019 vehicle efficiencies, leading to different relative impacts of the fuel required to power the additional electrical load. These real-world impacts appear to be on the order of roughly 5% lower than the BEV results, although the range of sensitivity is again much larger for the ICEs. For example, a 2000 W additional load is estimated to result in a 6%–24% increase in fuel consumption for the range of MY2019 ICE vehicles, whereas the same 2000 W load applied to the MY2019 BEVs results in a real-world electrical consumption impact range of 17%–30%.

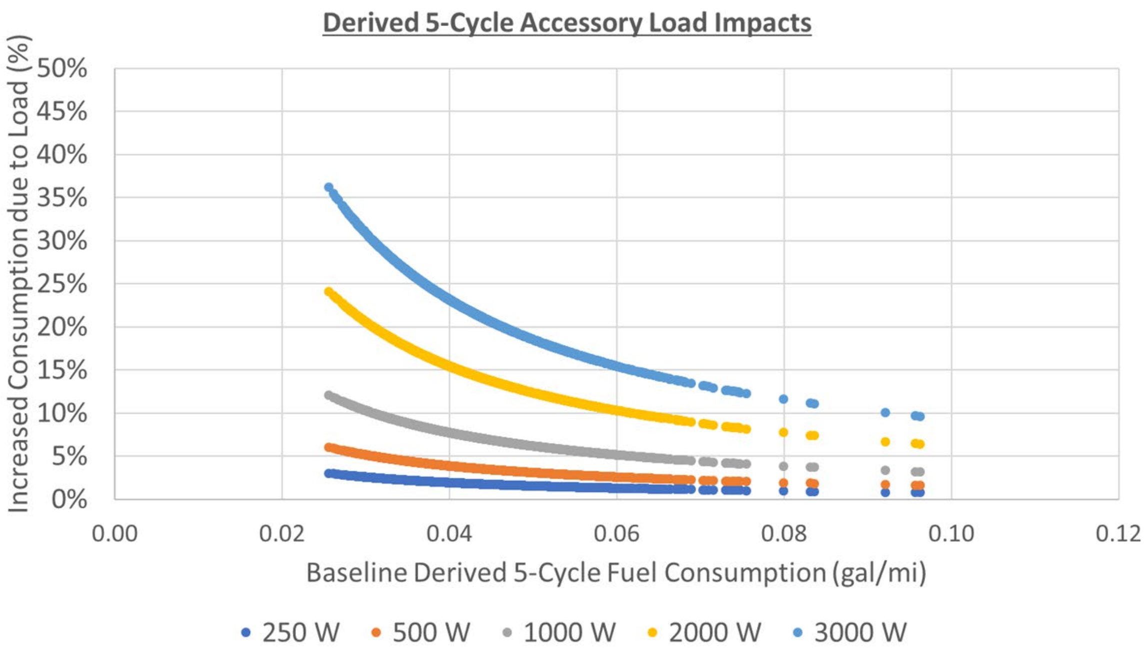


Figure 3-34. MY2019 ICE vehicle estimated real-world additional electrical load sensitivity.

3.1.7.2 In-Field Assessment of Automated Vehicle Electrical Loads during Typical Operation

- Field testing of a Cadillac CT6 with Super Cruise, a L2+ automation system, found automation system loads slightly above 100 W, including actuation, processing, and sensing loads.
    - The additional electrical loads changed minimally when Super Cruise was deactivated, suggesting that for lower-level automation capabilities the true accessory load penalty for certain eco-behaviors may be minimal if these systems are already in use for safer driving.
- Field testing of an automated vehicle prototype, provided by an industrial project partner, found automation loads ranging between 300W and 400W for functionalities including hands-free highway operation (L3) and fully self-driving operation and navigation at lower speeds (L4). These electrical load levels suggest that many automation functions may be implementable at loads lower than the 2-4 kW seen in recent driverless-capable pilot fleets.
- Issues such as how to implement safe and efficient system redundancy (and the associated electrical loads), as well as the electrical loads associated with cooling an automated vehicle's processing system, were also highlighted in the in-field testing.

The second component of this work sought to quantify the power consumed by the sensors, controllers, and actuators of a production hands-free automated driving system (L2+) as well as the power required for a L3/L4 automated vehicle development prototype. To support this assessment, a production 2018 Cadillac CT6 with "Super Cruise" advanced driver assist features[84] was selected for the L2+ case. The Super Cruise system uses multiple radars (a mix of long and short range units) fused with a forward facing camera and processing unit for its environmental perception system. This externally facing system is supplemented by an internally facing driver awareness camera and processing unit used to ensure continued driver engagement despite operating in hands-free mode as well as a GPS and mapping unit to ensure the vehicle is operating within its intended operational design domain (ODD). The Cadillac vehicle provides insights into current series production strategies, and the hands-free capabilities enabled by the Super Cruise system likely represent a minimum point at which certain eco-driving strategies may be implemented on a controlled access highway. For example, since the driver is already somewhat disengaged from specific maneuvers, the Super Cruise system could easily coordinate with other vehicles (assuming some form of V2V communication/coordination) to create spaces for merging vehicles to enter the highway, thus smoothing overall traffic flow.

In collaboration with project partner FEV[85], FEV's "Smart Demonstrator" vehicle[86,87], a 2017 Ford Fusion hybrid-based automated vehicle development platform for L3/L4/L5 sensor development and controls research, was selected as the L3/L4 assessment platform for this research. The Smart Demonstrator is equipped with a single NVIDIA DRIVE PX2 GPU-enabled processing unit in addition to a ruggedized PC and accompanying peripherals. The Smart Demonstrator utilizes the following sensors:

- 360-degree LIDAR (Velodyne VLP16)
- Six wide-angle 2 MP cameras (120 degrees)
- Two 2 MP front-facing cameras (60 degrees) for stereovision
- One narrow angle 2 MP front-facing camera (43 degrees)
- Dual-band front facing radar (>70 GHz wavelength)
- Precise two-antenna dGPS with RTK and IMU correction (accuracy up to 1.5 cm)

Each vehicle was instrumented with a large number of voltage and current sense points. Sense points were focused on overall vehicle automation system power consumption as well as on individual sensors, their controlling ECUs, and the actuators that they control. An array of additional sensors and cameras were used to facilitate and record the actual testing in order to better understand the surrounding operational conditions during testing. The results, though potentially similar to those for other systems, are specific only to those measured and to the specific suppliers of the sensors suites evaluated. Example sense points and instrumentation are shown in Figure 3-35, Figure 3-36, and Figure 3-37 below.

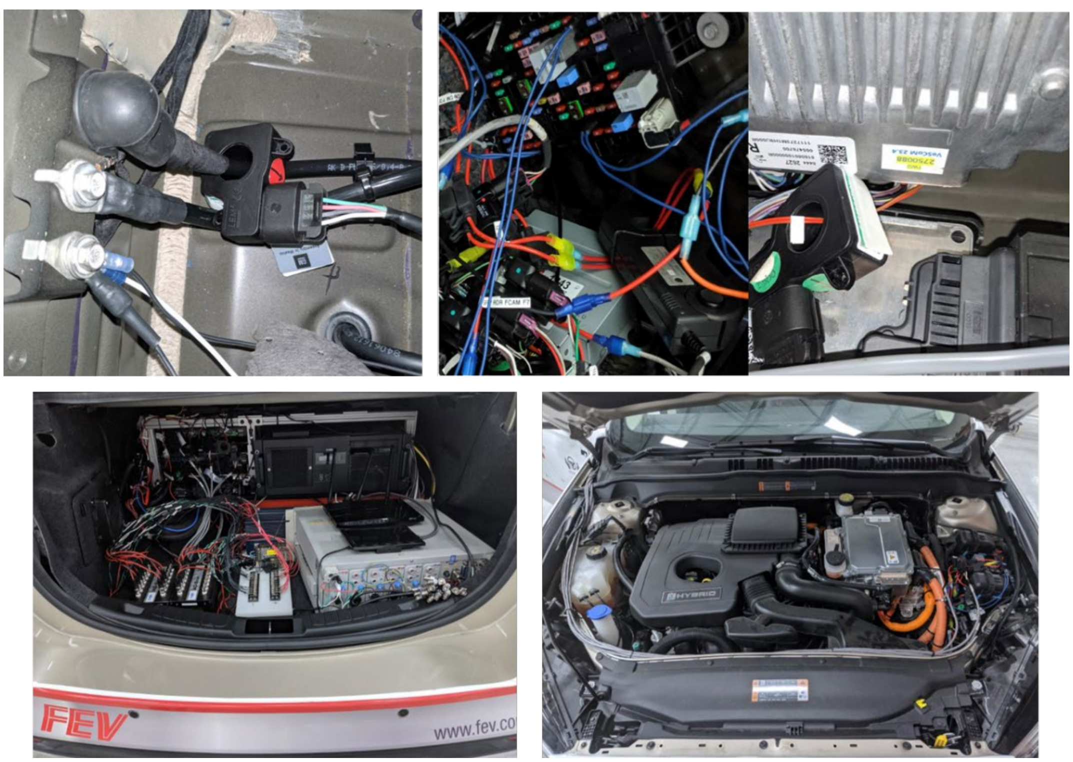


Figure 3-35. Examples of advanced driver-assistance system instrumentation and sense points.

An overview of the instrumentation for each vehicle is provided in Figure 3-36 and Figure 3-37:

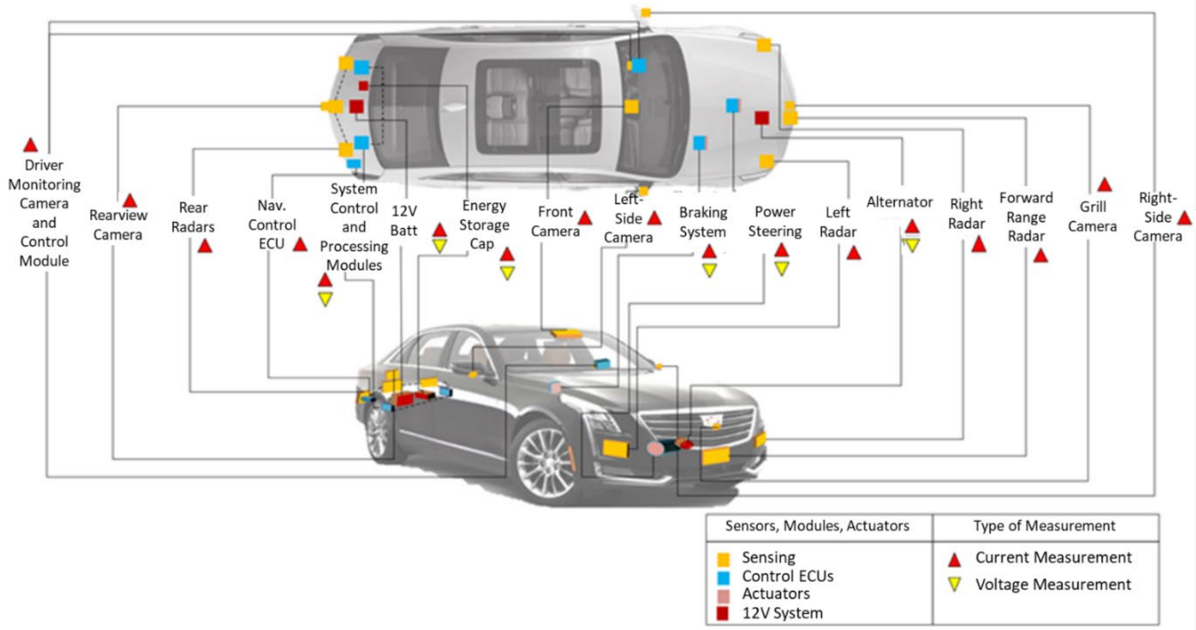


Figure 3-36. Cadillac CT6 Instrumentation Overview.

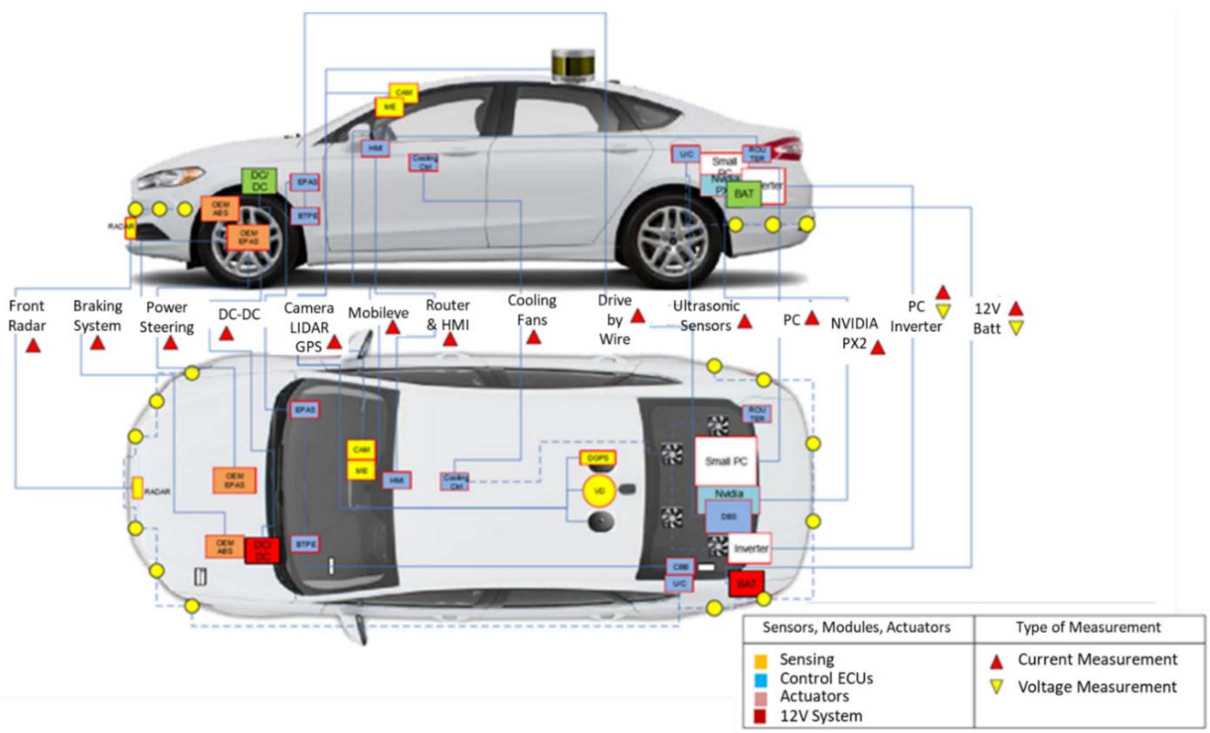


Figure 3-37. Ford Fusion HEV (FEV AV Demonstrator) Instrumentation Overview.

3.1.7.3 CT6 with Super Cruise — Highlighted Results

Controlled access highway driving with the Super Cruise system enabled resulted in an overall average measured automation-related power consumption of 101 W to 104 W. The sensors themselves consumed an average of 52 W, or roughly 50% of the total system load. The ECUs and processing support for the specific advanced driver-assistance systems (ADAS) features being reviewed consumed 35 W, roughly 35% of the total consumption. The actuators (electric power steering and braking) consumed an average of 14 W over the course of testing. The consumption results were consistent regardless of environment or complexity of the driving environment. Overall system and individual group usage are summarized in Figure 3-38 below, with significant individual contributor components shown in Table 3-4.

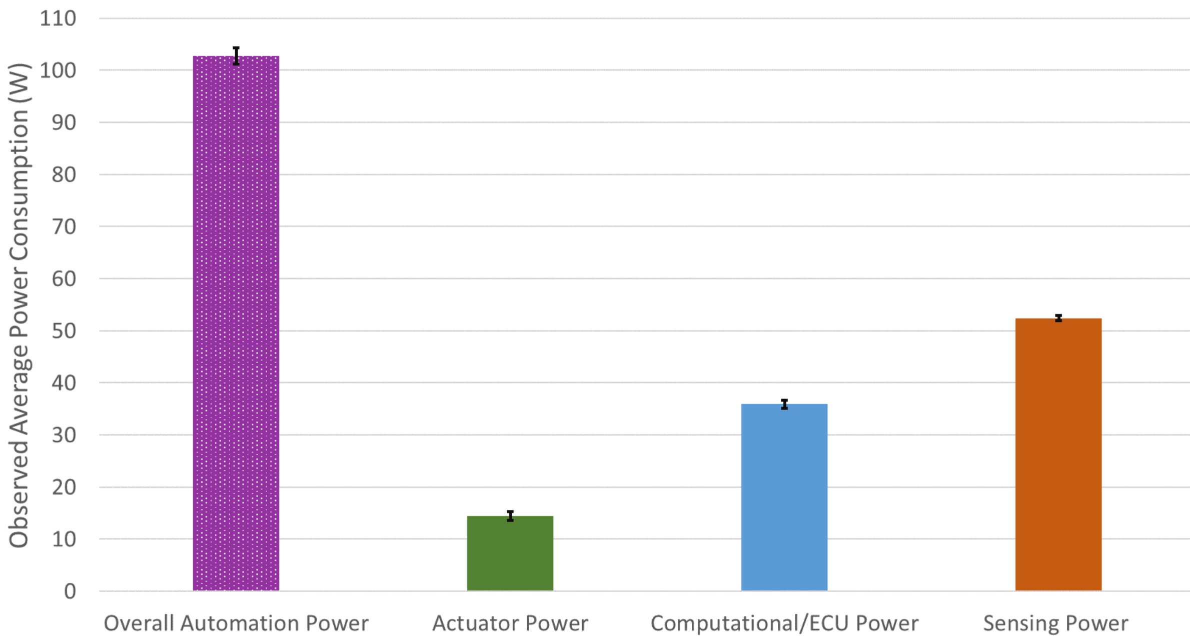


Figure 3-38: Super Cruise overall automation system and subsystem average electrical loads during operation on public limited access highways (95% confidence interval shown in error bars).

Table 3-4: Key Contributors to Observed Super Cruise On-Road Accessory Loads.

Component	Average Observed Power Consumption During Super Cruise Operation
Radar (aggregate)	40W
System control and processing modules (aggregate, two modules)	24W
Driver monitoring control module (DMCM) and camera	10W
Electric power steering actuators (EPAS)	10W
External cameras (aggregate) (driver monitor not included)	9W
Video processing control module (VPCM)	6W
Other loads	4W

The device that saw the greatest difference in power consumption due to activation of Super Cruise was the driver monitoring control module (DMCM) which varied by ~3 W, due to the illumination of the driver's face during Super Cruise operation to ensure driver attentiveness. Surprisingly, the additional electrical loads due to the vehicle's other ADAS-related sensors and processing changed minimally when Super Cruise was deactivated. This is likely due to the processing system and sensors being used for other safety and convenience features even during normal operation, suggesting that for lower-level automation capabilities, the true accessory load penalty for certain eco-behaviors may be minimal if these systems are already in use for safer driving.

While the overall average power consumption for the actuation systems was a relatively low 14 W, the specific duty cycle of the actuators is an important consideration when generalizing the actuator consumption for a wider range of operational profiles. More specifically, since the Super Cruise vehicle operates exclusively on limited access highways, moderate to severe steering and braking inputs are relatively minimal, and thus a relatively low average overall power consumption is to be expected. For maneuvers that required a large and rapid change in steering position, momentary excursions to power levels above 700 W were observed for the power steering system. These excursions occurred during non-Super Cruise operating periods when the vehicle's electric power steering assist system activated when transitioning between roadways or navigating parking lots. Although to a lesser degree, the braking system also showed momentary periods of elevated power consumption. While the average observed actuation electrical load of 14 W represents a minimal impact to overall vehicle efficiency, these excursions do represent an important requirement for overall system maximum power capability, particularly for an EV, in that these elevated loads must be considered when budgeting for overall battery power capability in a driverless-capable vehicle (or any vehicle for that matter). Figure 3-39 shows the steering and braking system actuation loads during a subsection of the Cadillac CT6 testing, with and without the Super Cruise system activated.

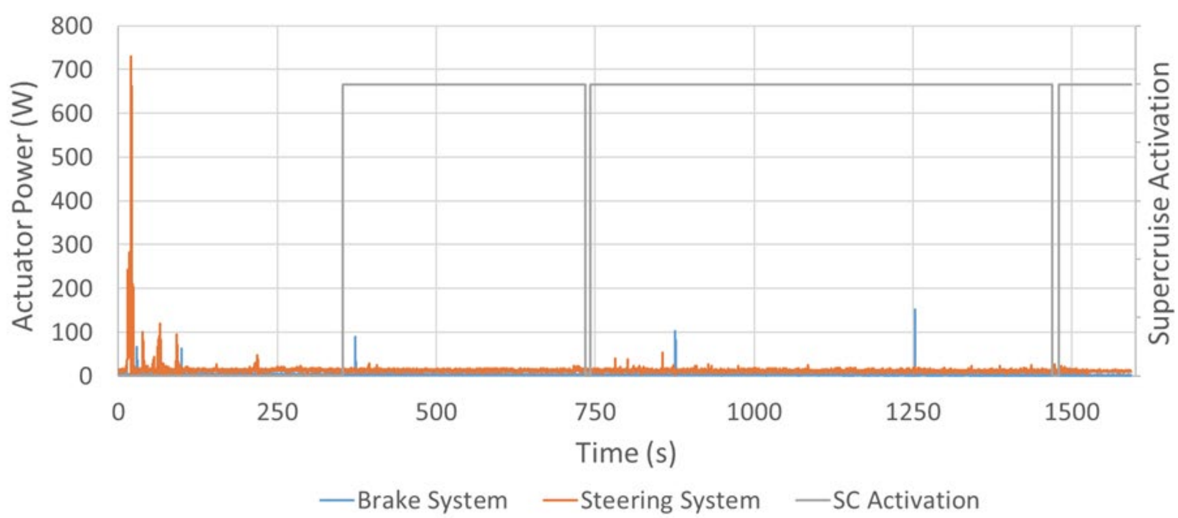


Figure 3-39. Example Cadillac CT6 braking and steering actuator loads during operation.

Another interesting observation about the Super Cruise vehicle is that it appears to utilize two fully redundant controllers to operate and supervise the automation system. Specifically, both active safety control modules (ASCM) are active during vehicle operation despite the vehicle's ability to operate using only one ASCM.[88] While each ASCM module utilizes between 11 W and 12.5 W (Figure 3-40), one can easily imagine that if fully redundant higher-power-consuming controllers were required for higher-level automation systems, this could result in a sizable increase in overall electrical load beyond what is needed for system operation. From this observation, it is clear that the amount of redundancy and capability for a safe driverless vehicle system is an important consideration not only for critical safety, but also for overall system energy usage. While not investigated in great detail for this work, since it primarily acts as a pass-through during normal operation, the

Super Cruise also has a capacitor-based energy storage and isolation system to power the ASCM modules in case of a loss of system power.

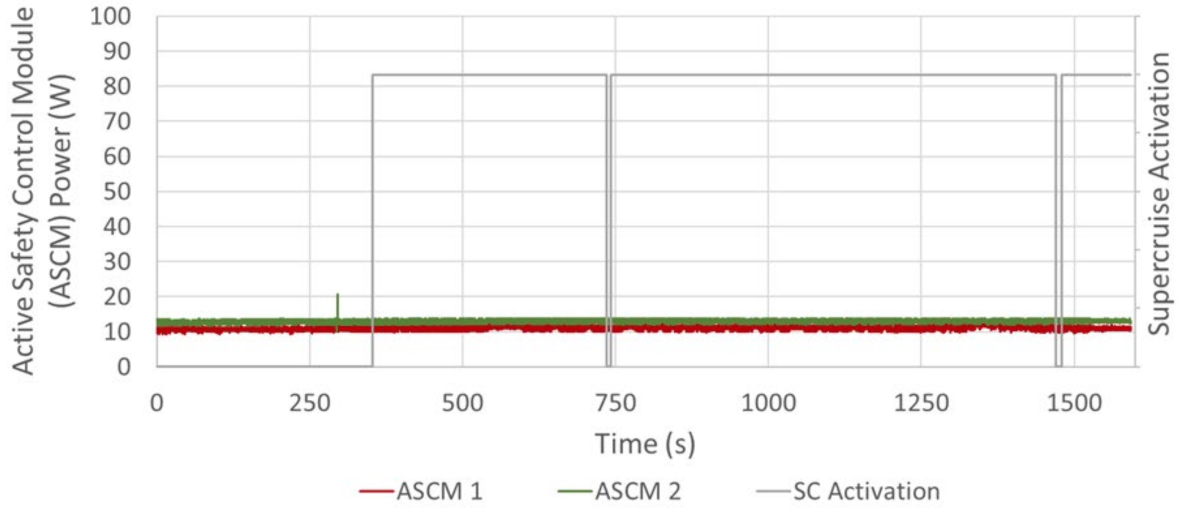


Figure 3-40. Cadillac CT6 active safety control module power consumption during vehicle operation.

3.1.7.4 AV Demonstrator — Highlighted Results

The FEV Smart Demonstrator was evaluated across two types of operation: 1) "Highway Pilot," which allows for hands-free highway operation requiring minimal driver attentiveness, similar to SAE L3, and 2) "Urban Pilot," which allows for driverless operation and navigation at lower speeds (similar to SAE L4). Summarized in Figure 3-41 below, the overall automation system for the demonstrator vehicle consumed 315 W during Highway Pilot operation and 380 W during Urban Pilot operation. Also noteworthy is the significant jump in processing loads, to 236 W and 257 W for Highway and Urban Pilot assist respectively. In contrast to the Super Cruise results, the processing loads now represent 70% to 75% of the overall automation system automation loads, providing support for the hypothesis that processing loads related to higher automation levels are driving the large in-field electrical loads seen in recent pilots (although loads for this testing are still well under the reported 2-4 kW levels). Given the much higher processing power levels, it also stands to reason that these systems will likely need supplemental cooling, and this is supported by the additional fan loads observed during testing: on the order of 19 W to 55 W depending on the use case and prior operating conditions. Although not to the same degree as the processing loads, overall sensor power consumption is also larger than the Super Cruise's due to the sensors utilized by the demonstrator vehicle. Average actuation loads appear to be roughly similar to the Super Cruise's, although the Urban Pilot operation shows slightly higher average loads (20 W vs 15 W), due to more and larger steering position changes.

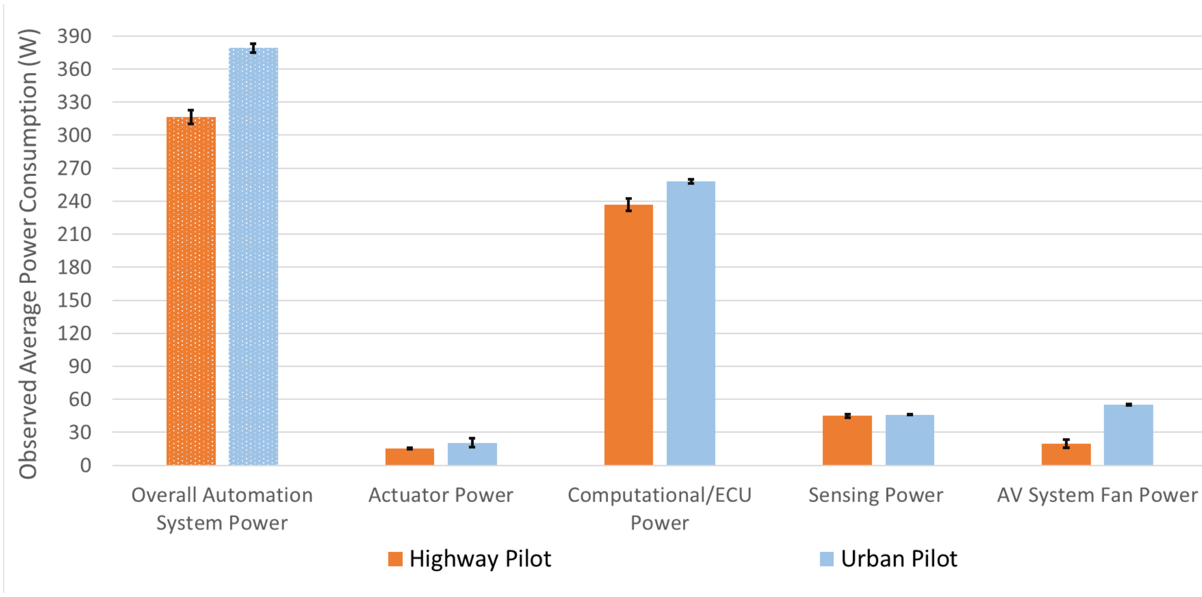


Figure 3-41. FEV Smart Demonstrator automation electrical loads during Highway Pilot and Urban Pilot operation on public roads (95% confidence interval shown in error bars).

Table 3-5 shows a consumption breakdown for some of the major components used in the demonstrator system. Interestingly, the PX2 processing system shows the same consumption across both operating modes, likely because the system processes nearly the same sensor information regardless of operating conditions (assuming the same frame rates in each case). In contrast, the system's PC, which is used for actions such as trajectory and route planning, shows increased power consumption in Urban Pilot operation. This observation suggests that it is important not only to consider the GPU-based image processing loads when refining an automation system, but the power draw required by certain planning and control algorithms may also drive additional loads. The second important observation, and one likely related to the differences in PC power consumption between the test modes, is the impact of thermal (cooling) loads as illustrated by the fan loads. Although the actual loads are likely dependent on the previous usage and cabin conditions during the specific tests, the load levels and their differences highlight that in addition to the loads associated with "running" an automation system, the thermal loads required to cool the systems are themselves an appreciable load.

Table 3-5. Key Contributors to Observed AV Demonstrator On-Road Accessory Loads.

Component	Average Observed Power Draw During Demonstrator Operation: Highway Pilot	Average Observed Power Draw During Demonstrator Operation: Urban Pilot
NVIDA PX2	127W	127W
PC	52W	81W
Cooling fan	19W	55W
Ethernet router and HMI	52W	45W
LiDAR, DGPS, OD camera	33W	34W
Other loads	32W	38W

While still a prototype demonstration vehicle, data and analysis from the FEV demonstrator point towards some promising insights and new research opportunities. More specifically, the vehicle is capable of most if not all of the eco-driving and coordination behaviors discussed elsewhere in this Capstone Report at electrical load levels between 300 W and 400 W, well below the 2 kW to 4 kW reported for recent pilot fleet testing. Combining the observed 315 W to 380 W additional electrical loads from the demonstrator testing with the sensitivity analysis presented in the previous section, overall real-world consumption impacts on the order of 5% or less may be achievable, which suggests that automation can become a net positive for vehicle efficiency when used to operate vehicles more efficiently and provide improved overall system efficiency. This testing also highlights the importance of considering the thermal loads associated with a given process in addition to the loads needed to operate the processing system.

3.1.7.5 Considerations for Driverless Capable Systems

While the 2-4 kW levels of electrical loads discussed in the introduction may seem high based on this work, applying the FEV demonstrator's much lower consumption loads across the board to represent driverless systems capable of operating across a much wider set of ODDs is not recommended. In fact, in consultation with several industry experts, a contrary opinion arose that, for driverless systems capable of operating across a wide range of ODDs, the 2 kW and above processing loads may not begin to decrease as quickly as many think. The reasoning is in part due to a continued need for higher resolution imaging/processing systems and a general need for more sensors for highly detailed situational awareness. This increase in resolution and sensor count leads to a significantly large input set to the automation system's processing subsystem, which will continue to require high levels of processing power. Moreover, the frame rate at which this information needs to be acquired and processed is also a significant driver of elevated processing loads, as electrical load can sometimes be estimated as proportional to calculations/operations per second.[89] While many automated vehicle functions can be done at loads well under the 2-4 kW required for a fully self-driving vehicle, it is not entirely clear when, how quickly, and to what degree the processing loads associated with fully self-driving vehicles will decrease. In addition, required system redundancy for safe operation may dramatically increase overall loads if fully redundant systems (and therefore processing loads) are required for failsafe vehicle operation. As would be expected, these topics are of immense academic and commercial research interest and contribute to the uncertainty of estimating expected electrical loads for a driverless-capable vehicle.

However, many companies, startups, academics, and OEMs are allocating significant resources to reducing the processing loads associated with fully driverless vehicles. ASIC, FPGA, and other specialized chip solutions have shown promise[90,91] for a significant reduction in overall processing, as supported by Tesla's fully self-driving computer's claimed 73 W processing load. Similarly, the self-driving industry is identifying additional methods for reducing average processing loads, such as dynamically modifying frame/processing rate depending on location and driving situation or activating sensors as needed due to changes in the driving environment.[92,93]

3.1.7.6 Summary

This work found that the energy consumption sensitivities related to electrical loads for a range of ICE and battery-electric vehicles vary significantly depending on cycle average power consumption and the type of driving where the loads are applied. For example, routes with a significant portion of idling will be especially strongly impacted by increased loads. These experimental efforts also observed real-world, in-use electrical loads for two different AV technologies. Field testing of a Cadillac CT6 with Super Cruise, a L2+ automation system, found automation system loads of 101-104W during on-road usage. Interestingly, the CT6's overall electrical loads changed minimally when Super Cruise was deactivated, suggesting that for lower-level automation capabilities, the true electrical load penalty associated with certain automated eco-driving capabilities may be minimal if these systems are already in use for safety driving. Field testing of an automated vehicle prototype, provided by an industrial project partner, found automation loads ranging between 300W and 400W for functionalities including hands-free highway operation (L3) and fully self-driving operation and navigation at lower speeds (L4). While the loads required for true driverless vehicle operation across a wide range of Operational Design Domains are still subject to significant uncertainties due to the rapid pace of vehicle development and refinement, the experimentally observed electrical load levels discussed in this report, suggest that many of the capabilities related to automated eco-driving may be implementable at electrical loads ranging from 100W to 400W, depending on the required capabilities.

3.1.8 Use Cases and Energy Characterization of Lower-Speed Automated Shuttle Applications

- The low operating speeds of current automated shuttles significantly increases the impact of accessory loads on overall per-mile energy consumption for these vehicles.
- Air conditioning loads nearly doubled the observed per-mile vehicle energy consumption in hot weather compared to cool weather operation.

Automated transit systems have existed in various forms for some time, but recent advances in self-driving technology have ushered in several new modes of vehicle operation with various levels of autonomy. Among the first commercially available vehicles featuring SAE Level 4 automation are low-speed automated electric shuttles. These small van-like vehicles generally feature room for about 12 passengers with a combination of seating and standing space. In line with their Level 4 automation designation, they generally do not feature steering wheels or pedal controls and may be permitted to run without operator intervention. Automated electric shuttles have the potential to reduce fuel use by displacing personally owned vehicle operation and substituting electricity for petroleum consumption, yet the usage profiles and energy consumption related to these vehicles is not widely documented. The CAVs Pillar collected energy consumption and operation characteristics of these unique automated electric vehicles and made the data available to researchers modeling future mobility scenarios. Directly related activities within SMART Mobility include the automated mobility district impacts modeling effort of the Urban Science Pillar (refer to the SMART Mobility Urban Science Capstone Report: Section 2.3 - Urban Infrastructure & Built Environment Synergy with Mobility) and the dynamic wireless power transfer feasibility analysis of the Advanced Fueling Infrastructure Pillar (refer to the SMART Mobility Advanced Fueling Infrastructure Capstone Report: Section 2.3 - Exploring New Paradigms Created by Automated-Vehicle Charging).

Three automated shuttle pilots agreed to participate in the data collection effort for this project — University of Michigan (U of M), Texas Southern University (TSU) and University of Utah (U of U). These pilots were selected because their owners were willing to participate in two-way data sharing, and their timing coincided with this project. Successfully connecting with multiple automated shuttle pilots resulted in performance data being captured over a range of state-of-the-art vehicle types, as observed under a set of differing real-world use cases and environments (rather than from the laboratory or simulated field applications). Daily recharge energy combined with daily mileage were the minimum data collected from each pilot to quantify daily energy consumption characteristics. Additional data were gathered as available.

The first data collection site was the University of Michigan, which operated a pilot with two Navya Autonom shuttles[94] equipped with custom data logging systems with Global Navigation Satellite System (GNSS) receivers to provide travel path and speed data. GNSS data were provided exclusively by this pilot, allowing for some additional analysis. These vehicles operated on a 1.2-mile-long round-trip route on the university's north campus in Ann Arbor, Michigan. The route was located on secondary campus roads with speed limits of 25 mph. Shuttles were continuously staffed by safety conductors to ensure proper operation and to manually navigate the shuttles if necessary. Both shuttles ran between north and south stations for six hours daily and were charged in an indoor bay during conductor lunch breaks and during the night. Shuttle operations were launched in June 2018.

Figure 3-42. Map of shuttle route at University of Michigan (courtesy of University of Michigan).

Per Navya specifications, the Autonom shuttle features a 33 kWh LiFePO4 battery pack and a 7.2 kW onboard charger. Climate control equipment includes dual 4.6 kW air conditioning units and a 3.4 kW heater. The curb weight is 2400 kg, and the gross vehicle weight rating is 3450 kg, yielding a 1050 kg payload carrying capacity.

Figure 3-43. Two Navya Autonom shuttles on the University of Michigan campus (courtesy of University of Michigan).

The second automated shuttle pilot the CAVs Pillar cooperated with was launched by Houston Metro at Texas Southern University in Houston, Texas in May, 2019. One EasyMile EZ10 Gen 2 shuttle was leased for this pilot. The vehicle was deployed on a 1-mile round-trip route on the university campus. The route was on the university's Tiger Walk, a paved pedestrian path, which is not open to regular motor vehicles. A dedicated shuttle lane was established on this path and the shuttle ran on weekdays for approximately 6-8 hours daily. The shuttle was charged in an indoor garage bay during mid-day breaks and at night. The shuttle was continuously staffed by an operator to ensure proper operation and to manually navigate the shuttle if necessary.

Figure 3-44. An EasyMile Gen2 shuttle, identical to the model used at TSU, is shown operating as part of a pilot in Salt Lake City, Utah.

Per EasyMile specifications, the EZ10 shuttle features a 30.72 kWh LiFePO4 battery pack and a conductive onboard charger. The vehicle was equipped with air conditioning units. The curb weight is 2130 kg, the gross vehicle weight rating is 3130 kg, and the payload carrying capacity is 1000 kg.[95]

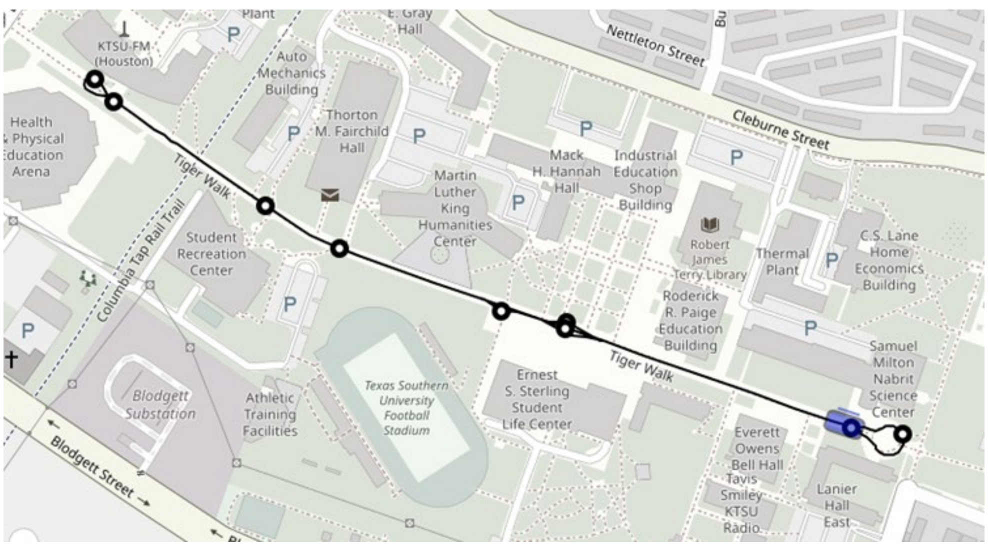


Figure 3-45. Map of Shuttle Route on Texas Southern University Campus (courtesy of EasyMile).

The Utah Department of Transportation and Utah Transit Authority launched the third driverless shuttle pilot the CAVs Pillar collaborated with at the University of Utah's campus in Salt Lake City, Utah in August 2019. One EasyMile EZ10 Gen 2 shuttle was leased for this pilot. At the University of Utah campus, the vehicle was deployed on a 1-mile round-trip route. The shuttle ran on weekdays for approximately 6-8 hours daily and was charged in an indoor garage bay overnight. The shuttle was continuously staffed by an operator to ensure proper operation and to manually navigate the shuttle if necessary. This shuttle is identical in specifications to the TSU shuttle detailed above.

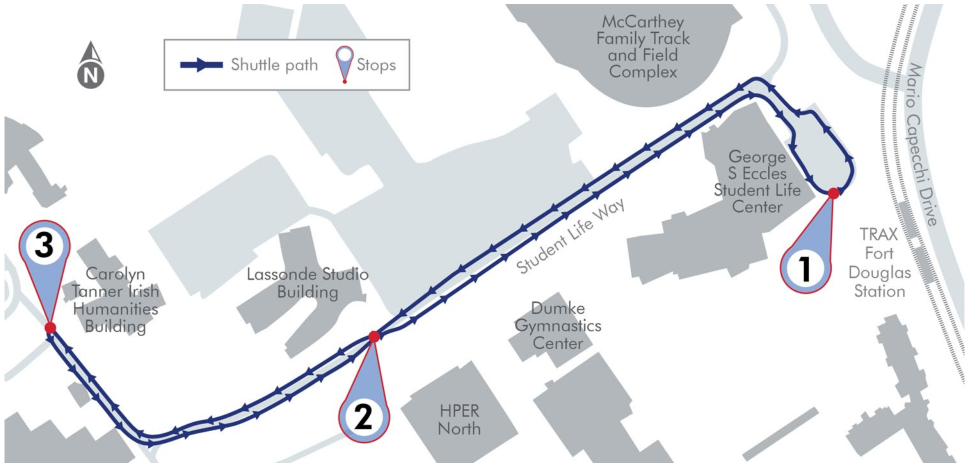


Figure 3-46. Map of the shuttle route on University of Utah Campus (courtesy of Utah DOT).

Charging energy delivered to each shuttle was collected by metering the charging circuits used exclusively to charge the shuttles. Distance traveled was collected via odometer logs provided by the operators or from GNSS data when odometer logs were unavailable. In the case of the University of Michigan pilot, daily operating distance and energy from the two shuttles were combined and averaged because it was not possible to discern which shuttle charged at which circuit. Travel distances were combined with the charging energy data and used to provide a daily snapshot of energy consumption and the routes travelled. Because the automated shuttles are on a fixed route, sensitivities affecting vehicle energy consumption, such as weather or speed profile, can be also explored from this dataset.

Substantive data collection and analysis were completed on the University of Michigan, Texas Southern University and University of Utah deployments. For each of these deployments, the monitored shuttles generally used most of their battery capacity during daily operation. The TSU EasyMile shuttle drove a median 24.2 daily miles, and the U of U EasyMile shuttle drove a median 21.1 miles daily. The U of M Navya shuttles drove 21.1 median daily miles per vehicle. These distances corresponded to daily run-times of approximately 6-8 hours. No doubt due to the very early nature and limited maturity of the technology, along with the prudence of cautious operation in mixed travel conditions (with pedestrians, bicyclists, etc.), the shuttles drive quite slowly (even below the 25-mph limit imposed on other low-speed vehicles such as neighborhood electric vehicles). When also factoring in the amount of time the vehicles spent stopped at pick-up/drop-off locations, the median daily average speed was 3.3 mph for the TSU shuttle, 3.0 mph for the U of U shuttle and 3.4 mph for the U of M shuttles. Distributions of daily average speed, which includes operating time when both moving and stopped, are shown for each vehicle pilot in Figure 3-47.

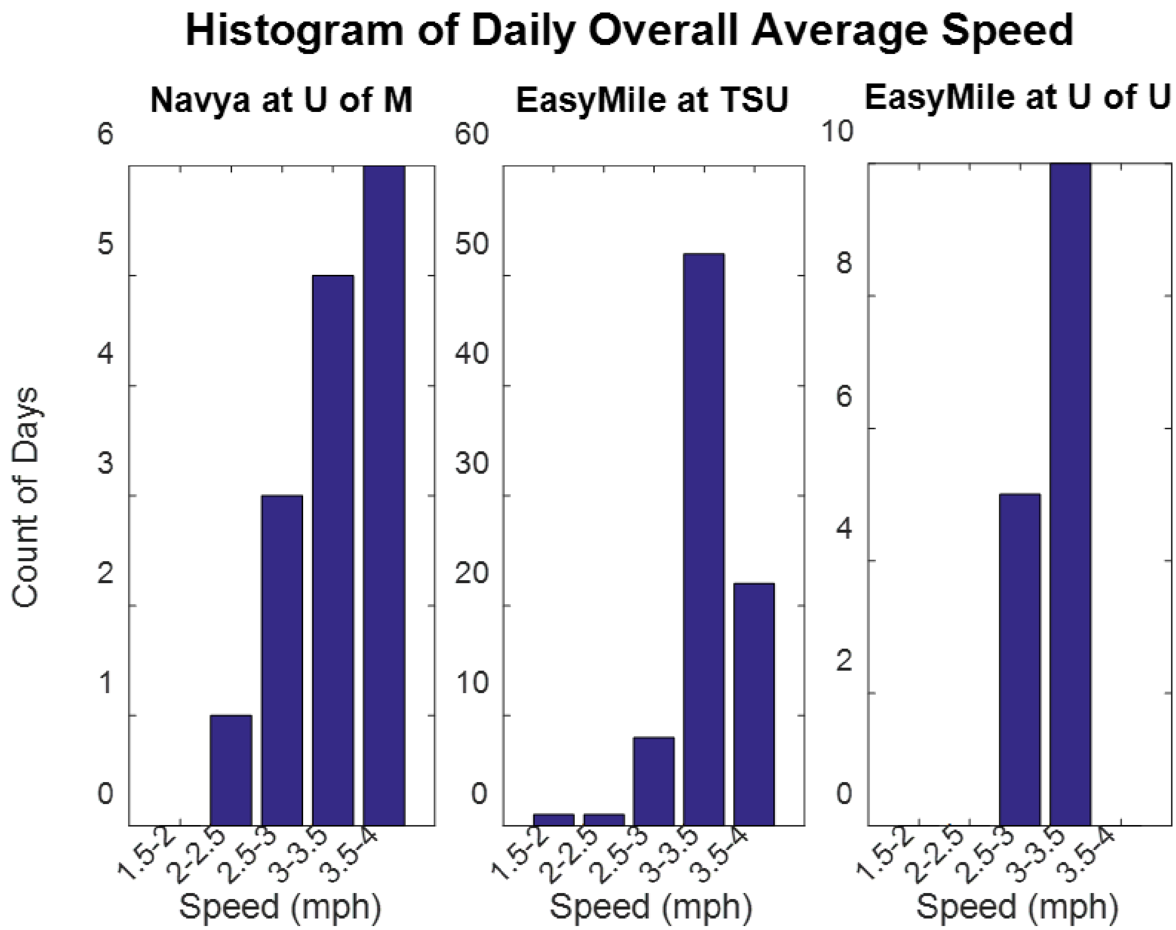


Figure 3-47. Distribution of Daily Average Speed for Each Shuttle Pilot.

The GNSS data from the U of M pilot enabled more detailed analysis beyond daily average speed calculations, including quantifying the proportion of time stopped and the average speed while moving. From one day of operation, March 25, for both shuttles, the moving average speed was observed to be 6.0 mph, with the vehicles stopped for 44% of the total operating time. The cumulative distribution of speed over that day is shown in Figure 3-48. In the entire U of M data set, the top speed observed was 13.6 mph.

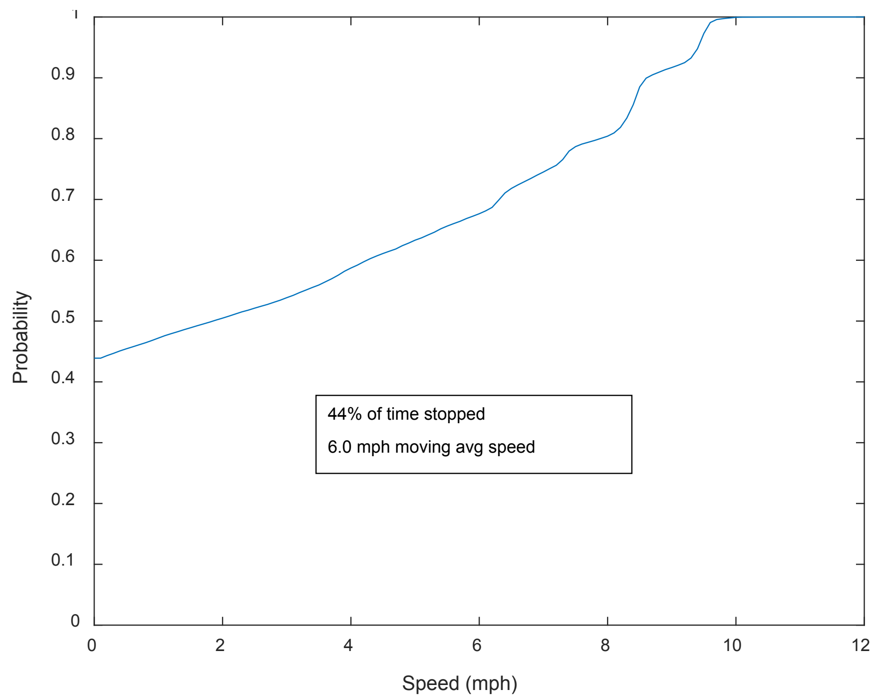


Figure 3-48. Cumulative distribution of U of M shuttle speed over a single day of operation for both shuttles.

Daily energy intensity was calculated for each shuttle for every day for which data were available and complete. The U of U data set, with 15 days of data, was gathered exclusively during summer months. The TSU data set, with 84 days of operation data, was collected from both summer and fall months, and while both hot and cool days were observed, there wasn't a clear delineation in seasonal temperature by date. The U of M data set, while small, includes results from both late summer (four days) and early spring (10 days), which have been displayed separately because there is a significant difference in seasonal energy consumption. The median energy consumption rate over a full day's driving was 1262 Wh/mi for the TSU shuttle, 1333 Wh/mi for the U of U shuttle, 1768 Wh/mi during summer days for the U of M shuttles, and 701 Wh/mi during spring days for the U of M shuttles. Because the operation of each pilot was managed differently, in different conditions, consumption data are not directly comparable between pilots or vehicle models. Rather, the range of consumption in varying climate and speed conditions can be considered for each pilot. Distributions of energy intensity for each pilot are shown, excluding outliers, in the figures below.

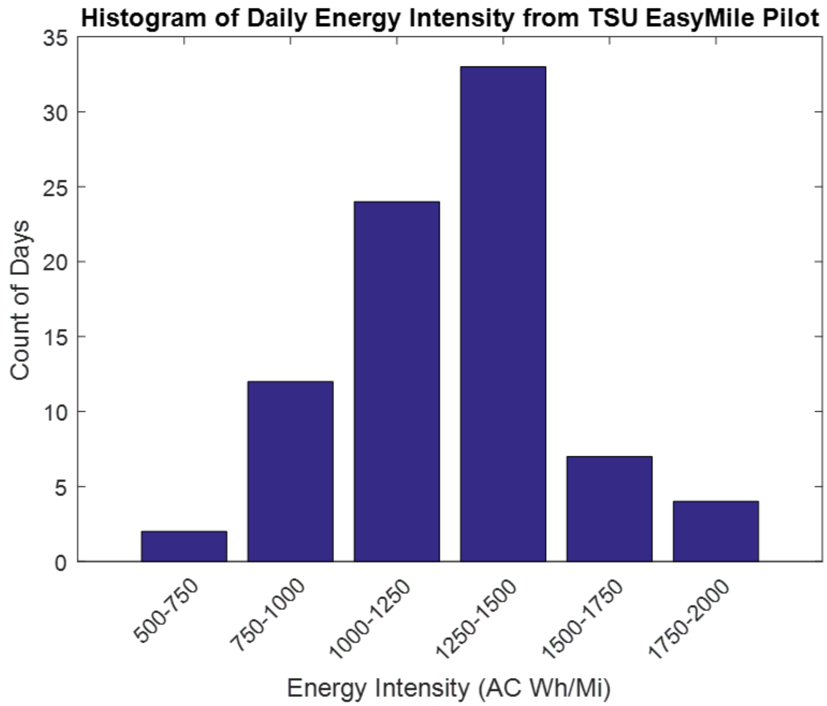


Figure 3-49. Distribution of TSU EasyMile shuttle energy intensity.

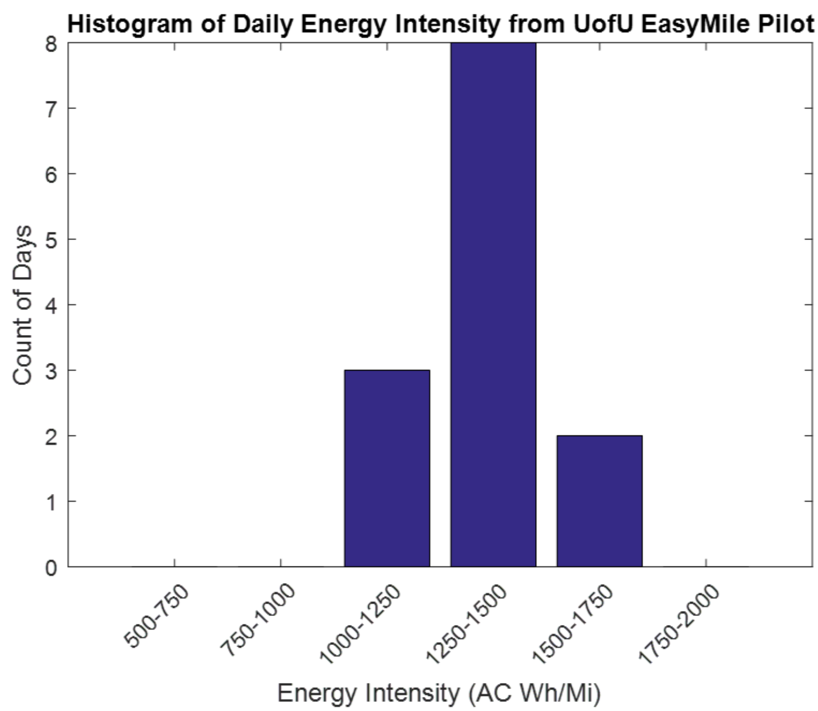


Figure 3-50. Distribution of U of U EasyMile shuttle energy intensity.

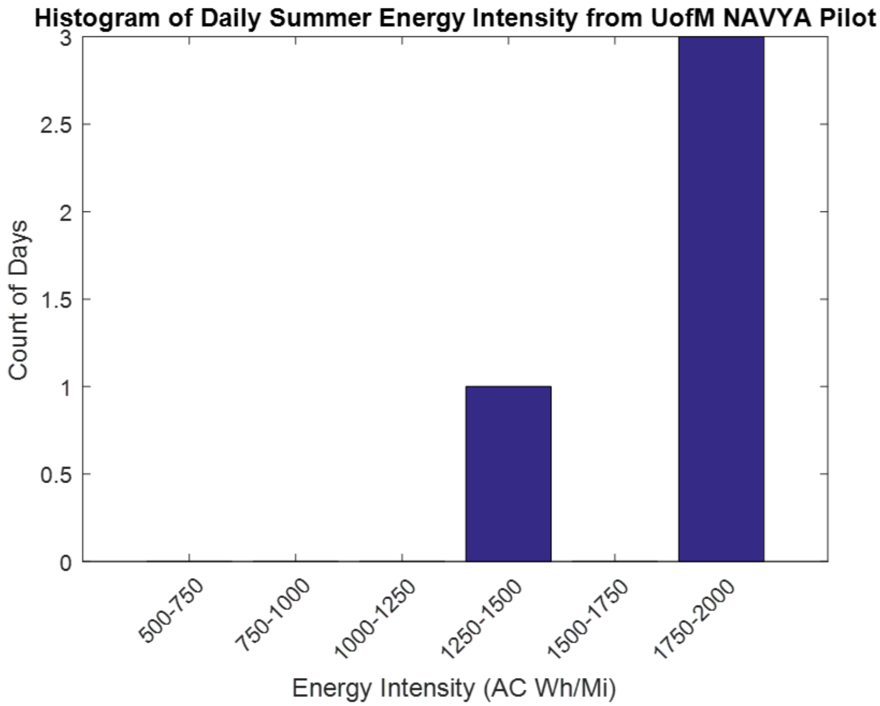


Figure 3-51. Distribution of U of M Navya shuttle energy intensity during summer operation.

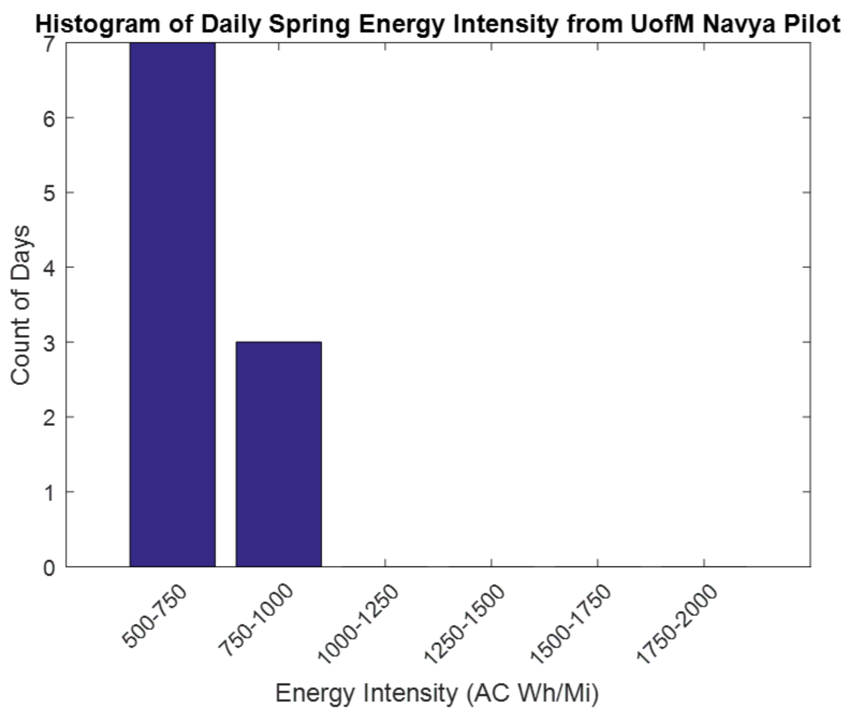


Figure 3-52. Distribution of U of M Navya shuttle energy intensity during spring operation

The automated shuttles that the CAVs Pillar studied are complicated vehicles used in routes that differ from conventional bus transit. They can be affected by several external factors, such as passenger loading and weather. Thus, it stands to reason that their energy consumption is a function of many externalities, in combination with their powertrain characteristics. Based on observations from other electric vehicle testing, it seems that these vehicles use a particularly high proportion of their energy on time-constant accessory loads, independent of the tractive effort required to move the shuttle. These types of time-constant loads, such as heating, ventilation and air conditioning (HVAC), have a great effect on vehicles with low average speeds.

To illustrate this concept, Figure 3-53 shows the energy intensity range for two simplified hypothetical vehicles along with the results from this study. The first simplified hypothetical scenario considers a vehicle with fixed tractive-effort energy intensity requirements of 400 Wh/mi, a 5-mph moving average speed, and a time-constant power requirement ranging between 500 and 5,000 W while operating over a 25-mile route. The area outlined by the blue line in the figure represents the varying energy intensity for this hypothetical vehicle scenario, with variation in the horizontal dimension caused by changes to the amount of time the vehicle spends at stops and variation in the vertical dimension due to the assumed upper and lower bound of the time-constant power requirements. The area outlined by the yellow line in the figure represents a similar scenario, where the same simplified hypothetical vehicle operates at a faster average moving speed of 10.67 mph with a corresponding increased tractive-effort energy intensity requirement of 500 Wh/mi (but the same range of time-constant power loads and proportions of time spent stopped), since varying the proportion of time stopped changes the overall average speed even when the actual moving average speed does not change. The data points from the shuttle pilots are also overlaid on the figure. Although simplified, these hypothetical vehicle examples illustrate how a decrease in average speed clearly increases per-mile vehicle energy consumption rates due to increased consumption by non-tractive, time constant accessory loads. This increase in consumption with a decrease in average speed is exacerbated as time-constant accessory loads increase. Potential future efforts to increase average daily operating speed for these shuttles may therefore lead to improved energy efficiency.

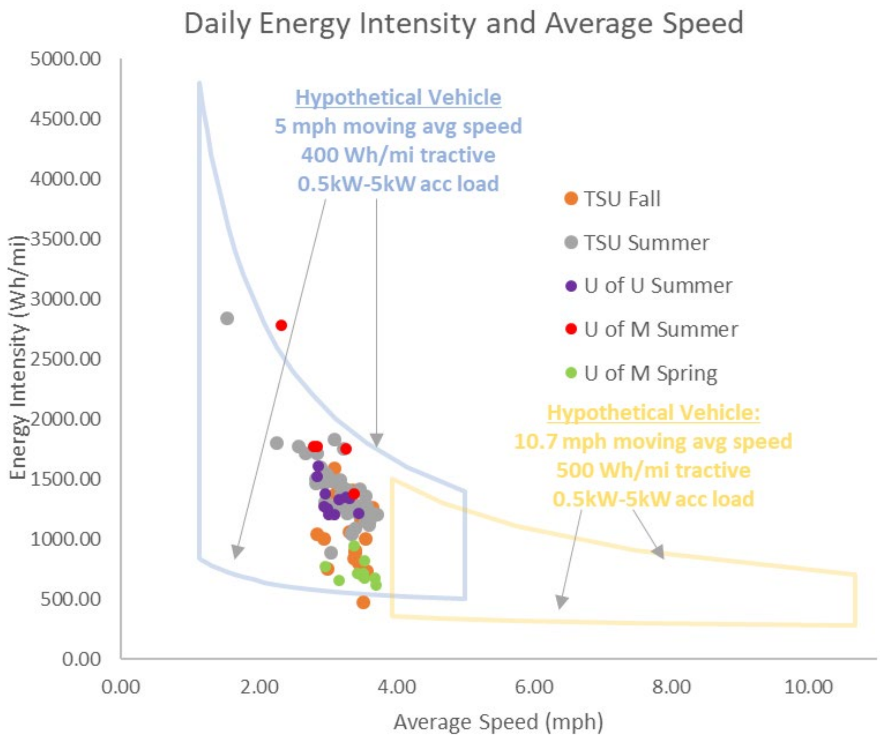


Figure 3-53. Daily energy intensity of each pilot shown relative to average daily speed, along with illustrated ranges of a simple hypothetical vehicle.

For further context, representative energy consumption rates were calculated for modern human-driven electric vehicles both smaller and larger than the automated electric shuttles. The larger vehicle comparison leveraged NREL's report on Foothills Transit's battery electric bus deployment, in which a fleet of 35-foot battery-electric transit buses (each with a roughly 27680 lbs curb weight) consumed an average of 2150 Wh/mi to 2170 Wh/mi while traveling at an average speed (including stops) of 8.57–10.6 mph.[96] The smaller vehicle comparison leveraged Idaho National Laboratory's report on the 2013 Nissan Leaf, showing that this vehicle (with a 3302 pound curb weight) consumed 275 Wh/mi when running the urban dynamometer drive schedule (UDDS) at 95°F with 850 W/m^2 of solar irradiation.[97] The UDDS has an average speed of 19.5 mph, with 17 stops over the 23-minute-long cycle.[98]

Although obtained from multiple deployment locations, the sample size for the collected automated electric shuttle operating data is small and primarily reflects summertime operation in hot conditions. Nevertheless, the U of M and TSU data shows a stark contrast in energy intensity between summer and spring or fall operation. This strongly suggests that HVAC loads for cabin cooling in hot weather account for a significant portion of the measured energy consumption demands, primarily because of the vehicle design, featuring many windows and large doors for passenger on- and off-boarding (and simultaneous air exchange between the cabin and outside environment). Figure 3-54 illustrates the effect of ambient temperature on energy consumption observed for the TSU EasyMile pilot in Houston. Hourly temperature data were retrieved from NOAA's Climate Data Online database for the station nearest to TSU, about two miles away at the Texas Medical Center. Temperature readings between 8 a.m. and 8 p.m. were averaged to produce daytime daily averages to match the operating schedule of the shuttle. The lowest energy usage occurs on mild days, with more energy consumed as outdoor temperature increases or decreases from the band of comfortable temperature.

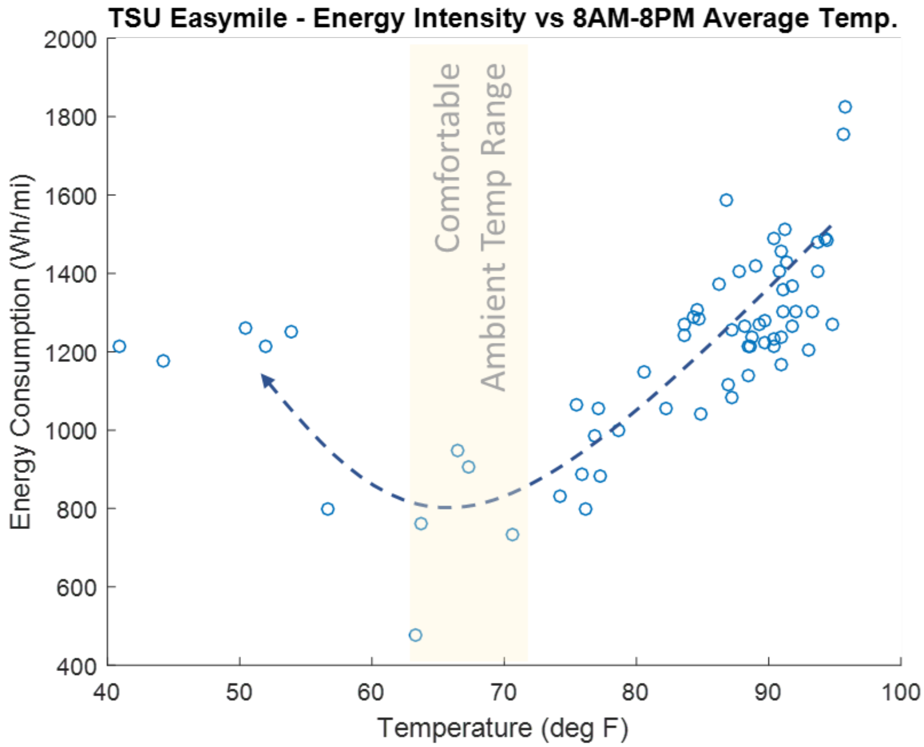


Figure 3-54. Daily energy intensity of the TSU pilot relative to daily daytime average temperature for a subset of days with average speed above 3 mph.

This data was provided to SMART Mobility modelers seeking to better ground their assumptions for modeling future automated shuttle scenarios and for optimizing potential wireless charging systems to serve such transportation scenarios. A deeper understanding of the energy-flow attributes for these self-driving vehicles could be obtained by instrumenting the vehicle battery, powertrain, and individual subsystems during operation and collecting data over a range of different operating conditions.

3.2 CAV-Specific Modeling and Simulation Methodology and Approach Refinements

In order to evaluate new transportation technologies such as connectivity, automation, sharing and electrification at different levels of fidelity and scale (i.e., from individual vehicles to entire metropolitan areas) multiple approaches and simulations were refined to comprehend the complex dynamic interactions and capabilities of CAV technologies. With this outcome in mind, the following subsections highlight adaptations and additions to DOE's advanced vehicle modeling portfolio with the goal of incorporating CAV technologies into a robust and validated environment of modeling and simulation tools. Specific adaptations discussed in this section include: 1) improvements to traffic modeling tools (micro-simulation) to incorporate mixed fleets of manually and automatically driven vehicles within a particular traffic scenario or environment, 2) an environment for simulating and optimizing the controls of multiple proximate vehicles with full powertrain models while comprehending and incorporating (when applicable) the interactions between these vehicles and their environment, and 3) CAV-specific refinements to regional-level modeling tools relating to traffic flow models, representation of vehicle agents, and implementation of resource allocation and optimization routines related to specific CAV technologies and capabilities.

3.2.1 RoadRunner: Trip-Level Simulation of Powertrain and Driving Dynamics for CAVs

- To help researchers and engineers develop energy saving algorithms that rely on a combination of powertrain controls, driving automation, connectivity, and sensing, a simulation tool called RoadRunner was developed to simulate, in the same environment, multiple connected and automated vehicles with full powertrain models as well as the interactions between vehicles and their environment.

One significant way in which CAVs can produce energy savings is through better vehicle speed and/or powertrain control at the individual or multi-vehicle level. Perception sensors and connectivity provide increased awareness of the surrounding environment and enable control optimization, while automation provides the necessary level of controllability for the application of the optimization. In order to research these topics (see Section 3.4.1), CAV Pillar researchers developed RoadRunner[99], a tool dedicated to the development and evaluation of energy-focused CAV controls.

RoadRunner is uniquely suited to energy-focused CAV control research and complements powertrain and vehicle system energy-efficiency research and traffic flow microsimulation models. Typical powertrain and vehicle system energy-efficiency research relies on specific drive cycles (i.e., predefined speed as a function of time). This approach is not suitable for CAVs, where the vehicle itself dynamically decides its own speed based on its environment. Traffic flow microsimulation tools, on the other hand, focus on the dynamics of interactions between a large number of vehicles on a corridor or a small road network rather than on individual vehicle control.

RoadRunner can simulate, in the same environment, multiple vehicles with full powertrain models as well as the interactions between vehicles and their environment. RoadRunner uses powertrain models from Autonomie[100,101], an established state-of-the-art vehicle energy-consumption simulator developed with U.S. DOE support, and adds new capabilities, such as multi-vehicle simulation, models of road characteristics, causal models of human driving, "vehicle to everything" (V2X) communications, and sensors. In short, it is designed to help researchers and automotive engineers develop energy saving algorithms that rely on a combination of powertrain controls, driving automation, connectivity, and sensing.

Figure 3-55 illustrates a typical RoadRunner workflow. The user first defines a scenario: the route, the number of vehicles, the type of vehicles, and the type of CAV technology for each vehicle. RoadRunner then automatically builds the Simulink diagram. Intersections are modeled either as stop signs or traffic lights, connected or not. Each vehicle is composed of an Autonomie vehicle plant model and supervisory controller, driver and/or longitudinal dynamics controller, with car-following and free-flow driving logic. An aerodynamics block computes the drag reduction coefficient based on relative position and inter-vehicle gap. Finally, the position along the route is computed, and signal routers allow the proper flow of information between the simulated agents (vehicles and intersections), so that each vehicle/driver receives only the information relevant to its position. Once the diagram is built and initialized, RoadRunner runs the simulation and post-processes the results to facilitate analysis by the user.

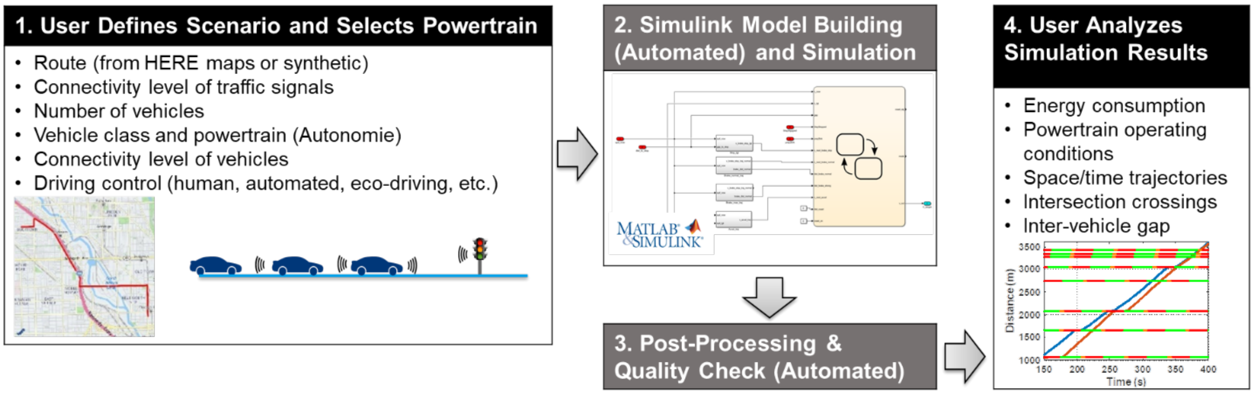


Figure 3-55. RoadRunner workflow to simulate a CAV scenario.

The development of RoadRunner involved two complementary tracks. On the one hand, the software back end was developed to allow easy setup, running and analysis of complex large-scale simulations, tapping into the research team's experience in the development of Autonomie. At the same time, CAV and baseline models were developed, integrated in RoadRunner, validated, and applied to analyze energy impacts of different scenarios, as described further in this report (3.4.1.1).

3.2.2 Micro-simulation and Traffic Flow Modeling for CAVs and Mixed Fleets

- In order to better understand the interactions between CACC and manually driven vehicles, microsimulation improvements were completed, including: 1) detailed and expanded operational models of CACC vehicle behavior based on field experiments, 2) improved modeling of manually driven vehicles interacting with CACC vehicles (i.e., human drivers operating near CACC strings), and 3) improved anticipatory lane changing models for both CACC and manually driven vehicles.

The market penetration of AV/CAV will likely be a long and progressive process. Therefore, mobility and energy consumption evaluation/prediction will need to consider a range of mixed AV and manually driven traffic scenarios, which will require the simulation of mixed traffic. Within this work, "car-following" models for cooperative adaptive cruise control (CACC) and autonomous (but not connected) ACC-based systems were implemented for both cars and heavy-duty trucks and calibrated directly from experiments on full-scale cars and trucks.[102,103] The developed CAV vehicle-following models capture the dynamic interactions between different CAV strategies and manually driven vehicles, which is the foundation of microscopic simulation-based analysis. If these foundational models of dynamic interactions are incorrect, the microscopic mixed traffic simulations built on these models will generate biased (or incorrect) results.

Stochastic microscopic simulation tools (microsimulation) for traffic flow modeling deploy analytical algorithms to describe vehicle behavior, including car following and lane changing, and are a critical component in understanding the traffic flow and efficiency ramifications of various CAV operating strategies for a vehicle and its surrounding traffic environment. Much of the microscopic simulation research discussed in this work builds upon a set of traffic microsimulation models that were developed at the University of California's Partners for Advanced Transportation Technology (PATH) program, based on the FHWA's Next Generation Simulation (NGSIM) oversaturated flow model[104] implemented on the Aimsun microsimulation platform[105] for baseline traffic. These revised and updated models include many enhancements, providing more realistic representations of normal drivers' car-following and lane-changing behavior as well as the expanded set of behaviors for ACC and CACC modeling.

Although CACC microsimulation modeling has attracted considerable research effort in the past few years, there are important model aspects yet to be developed for better CACC behavior representation. Many existing studies have analyzed CACC operations on a two-lane controlled access highway, without considering the lateral interactions of vehicles. Alternatively, some researchers have depicted the car-following and lane-changing behaviors of both manually driven vehicles and ACC/CACC vehicles using the same behavior model with different model parameter settings. Such a method fails to consider the differences between the two vehicle classes in terms of their distinct ways of acquiring data, processing information, and making driving decisions. In most of the existing studies, the CACC speed control algorithm was the only model used to depict the car-following behavior of CACC vehicles. However, drivers of CACC vehicles will typically take over the vehicle's lateral and longitudinal control when they need to make lane changes, yield to other lane changers, and apply emergency braking for collision avoidance. With these issues in mind, CACC models need to be improved such that they can describe situations in which a subject driver turns on or off the CACC controller during the car-following and lane-changing process. The model also needs to explicitly describe the car-following behaviors of the CACC controller as it switches among different control modes (e.g., constant time gap regulation or constant speed regulation control) under different roles in a CACC string (e.g., string leader or string follower). Moreover, the realistic modeling of CACC vehicle behavior also requires the enhancement of human driver models. The human driver models should be refined to capture a driver's lane changing preparation, gap searching, and lane changing maneuvers as the driver tries to merge into a target lane occupied by CACC vehicle strings.

To address these challenges, the CAVs Pillar developed a CACC modeling framework based on the NGSIM oversaturated flow human driver model and the CACC car-following model derived from the CACC field tests mentioned above. The models were enhanced by developing new algorithms that can reproduce the complicated interactions of CACC vehicles and manually driven vehicles in multi-lane controlled access highway segments.[106] Particularly, the addition of an anticipatory lane-changing algorithm and the CACC operation rules form a modeling framework to realistically depict the car-following and lane-changing behaviors of CACC vehicles in mixed traffic under the influence of the CACC management strategies. The lane-changing component is important because it considers the complex lateral interactions between the automated vehicles and manually driven vehicles. With these modifications and expanded capabilities, the models are now ready to reproduce the traffic dynamics that are likely to appear in multilane highways, while most existing studies consider CACC operation only in hypothetical two-lane highway scenarios. In addition, the modeling framework can describe the behaviors of CACC vehicles under the influence of specific CACC operation strategies relevant for improving overall traffic flow and corridor fuel consumption, the primary goal of the SMART Mobility Consortium.

3.2.3 Regional-Level Model Adaptations for CAVs

- At the regional level, CAV-specific modeling modifications and improvements include: 1) development and implementation of updated mesoscopic traffic flow models sensitive to CAV impacts, 2) implementation of vehicles as agents (especially driverless vehicles), including scheduling and operations, and 3) implementation of resource and scheduling constraints at the household level relating to vehicles both individually owned and shared as well as automated or non-automated.

Historically, existing transportation-related models have looked at different aspects of the transportation system (travel demand, traffic flows, emissions, etc.) independently. The evolving complexity of regional-level transportation networks has led to the integrated modeling of travel demand and network supply, as opposed to a sequential process. In particular, agent-based models (ABMs) capture these interactions from the perspective of a particular agent that engages in activities (demand) based on time-dependent travel times for the different modes available (supply) in such a way that demand and supply are mutually dependent. In ABMs, each agent is represented by multiple models that ultimately define several decisions, from long-term decisions, such as car ownership, to short-term decisions, such as activity location, departure time, mode, and route for a forthcoming trip.

Specific to the regional-level CAV work done by the CAVs Pillar, the POLARIS agent-based transportation systems simulator[107] was adapted and used for analysis. POLARIS is a high-performance, open-source agent-based modeling framework that can simulate large-scale transportation systems. It features an integrated travel demand, network flow and traffic assignment model in which multiple key aspects of travel decisions (activity planning, route choice, and tactical-level driving decisions) can be modeled simultaneously and in a continuous, fully integrated manner. POLARIS models individual decision making at long-term, mid-term and within-day time frames for the various decisions that are represented. The mid-term and within-day travel behavior decisions are captured in a computational process model representation of decision-making that captures the process of individual activity episode planning and engagement. These decisions are constrained by long-term choices such as home/workplace location and household vehicle, which in turn influence activity and travel episode planning and realization.

The network model includes a mesoscopic representation of vehicle movements based on the Newell's kinematic wave model[108] with updates for representing interactions with traffic control infrastructure. The traveler agents in the model can react in real time to changing or unexpected network conditions due either to direct observation or through information provided, using an en-route rerouting and replanning model. For long-term choices, the fleet definitions within POLARIS can come either from external market penetration forecasts coupled with baseline vehicle registration data, or from household level choice modeling. An additional CAV technology choice step is implemented using models based on stated-preference survey data[109] to determine the willingness to pay for various levels of CAV technology for household vehicles.

Analyzing mobility and energy impacts from future CAV technologies at the regional scale required substantial development of the POLARIS framework relating to the traffic flow models, representation of vehicle agents, and implementation of resource allocation and optimization routines related to CAV-specific studies and implementation updates. The mesoscopic traffic flow model has incorporated link capacity modification functions from empirical studies and microscopic traffic flow studies to represent CAV impacts over a range of penetration levels under a variety of configurations (e.g., merging sections, on/off ramps, lane reductions, etc.), based on a clustering analysis using observed highway data from loop detectors.[110] The link fundamental diagram within each cluster is then updated using microsimulation analysis.

The POLARIS behavioral simulator has also been significantly updated to incorporate a new household vehicle sharing optimization model, which seeks to determine optimal levels of vehicle sharing when the vehicle is allowed to reposition itself. The optimization utilizes an improved version of the model developed within the SMART Mobility Consortium.[111] The model assumes that households with a fixed number of fully automated vehicles (all household vehicles are assumed to be AVs for those willing to pay) are able to schedule the vehicle pickups in such a way to minimize total household costs. The AVs are able to reposition themselves between trips, and multiple household members can share the same trip if it is feasible. Additionally, the AV can travel home to avoid parking costs at any activity destination. The costs to the household include:

- Energy costs associated with each loaded and unloaded trip based on the travel distance
- Value-of-time cost due to trip diversions and wait time for coordinating shared rides
- Parking costs to wait at the destination
- Taxi or transit costs if vehicles are not able to service trips
- Vehicle ownership costs (or lack thereof)

The optimization routine described above is implemented using the Gurobi API[112] and is called for every household agent in the POLARIS simulation after the activity patterns are generated. The activity attribute flexibility model implemented in POLARIS is used to determine the start time and duration thresholds, with inflexible activities having low thresholds and highly flexible activities having higher thresholds. The exact level of the thresholds is left as a scenario parameter, with the default values of 5 minutes for low flexibility and 60 minutes for high flexibility. POLARIS also provides the optimization model with time-dependent travel times that are updated throughout the simulation run in order to ensure that schedules resulting from the optimization are consistent with those generated by the travel simulator. Finally, the new repositioning, or dead-heading, trips generated by the model are then simulated in POLARIS to analyze this additional source of increased demand.

For platooning simulations (discussed in Section 3.4.3.3), an algorithm[113] previously developed by Argonne researchers was adopted and integrated into POLARIS. The model tries to form platoons of vehicles, minimizing the energy consumed while meeting travel demand (for platooning-enabled vehicles) from POLARIS, and coordinates the vehicles' movements in the formed platoons. The POLARIS traffic simulator was modified to be able to update vehicles' routes to match their platoon head when they participated in a platoon, while accounting for the wait time to join a platoon. To improve efficiency, only expressway links of each trip were considered for platooning evaluation, and a new component, the platooning controller, was developed to optimally route platooning vehicles once they have entered a platoon. Therefore, the model first uses the POLARIS router to find a route from trip origin to a point where the platoon can be joined (the entry point, which is usually an on-ramp link), and then a route from where the vehicle exits the platoon and control is handed back to the POLARIS traffic simulator/router (the exit point, which is usually an off-ramp link) to the trip destination. The route from a vehicle's platoon entry point to a vehicle's platoon exit point are determined by the optimization algorithm. The optimization model then merges these three routes and generates an updated trajectory. The trajectory is assigned to the vehicle when it is loaded into the network, and then traffic simulation continues with its regular steps to move the vehicle. To accommodate the waiting times of the coordinated platooning movements, the traffic simulator code was modified so platooning vehicles could wait the amount of time requested by the optimal solution. For all cases, the expressway entry node is where vehicles wait to join the platoon; however, it may be possible for vehicles to wait at other points on the expressway to facilitate platoon formation.

Expanding upon the deep foundational capabilities enabled by ABMs, several CAV-centric adaptations and improvements were performed within the CAVs Pillar to better simulate the implications of CAVs on both overall traffic as well as household demand and mobility choices. Together, these changes help in more robustly integrating CAVs into a larger research and analysis portfolio.

3.3 Corridor-to-Regional-to-National Level Impacts and Sensitivities of Connectivity and Automation

Research findings in this section address the CAVs Pillar's second research question: "**What are the GHG, energy, technology and usage implications of connectivity, automation, and the combination of both technologies?**" As discussed in the Introduction and National Level Impact Synthesis sections of this report, there is significant uncertainty regarding the expected outcomes of widespread CAV introduction into today's transportation systems. Additionally, the dynamics of automated and/or connected vehicles operating in parallel with manually driven vehicles is also a topic of great uncertainty. These uncertainties lead to widely varying expectations for both the benefits and challenges associated with CAV introduction. Moreover, the behavioral sensitivities and key modeling assumptions leading to the range of expected impacts are also not widely established or documented with consistency. These issues are further complicated by the fact that many diverging possible future technology implementation scenarios need to be assessed in a coordinated manner and that these impacts ultimately need to be aggregated into a set of national-level impact estimates to better assess the impacts of CAVs from an overall energy and technology perspective.

In the context of these issues, **this section seeks to discuss research focusing on the impacts of CAVs when introduced into a current and near-term transportation system** as well as develop tools and insights regarding future CAV deployment and mobility market dynamics as well as methods to aggregate detailed results into a national-level impact assessment. Beginning with research into the traffic dynamics of 100% fully automated vehicles as well as mixed scenarios of CAVs and manually driven vehicles, this section then seeks to identify regional-level CAV implications. The section then transitions to more exploratory tools and insights regarding CAV transitions scenarios and dynamics and national level impacts and sensitivities to CAV technology implementation.

Key section insights and results include:

- At the freeway corridor level, automation without V2V connectivity (as represented by ACC) may lead to more congestion and increased consumption due to traffic instabilities created by the unconnected automation systems and the required following behaviors and distance associated with a lack of information from surrounding vehicles. In contrast, CACC, which is enhanced by V2V communications shows increasing benefits to both congestion and consumption as market penetration increases, ultimately, removing most if not all traffic congestion at current demand levels for this simulation study.
- At the regional level, CAVs have some congestion relieving effects when no assumption of value of travel time (VOTT) change is made (i.e., low rebound). However, as VOTT is reduced (via higher levels of vehicle automation or other means), significant travel increases can occur. For example, a preliminary investigation in the Chicago area showed that a 50% reduction in VOTT shows a 48% increase in vehicle hours traveled (VHT) and 45% increase in vehicle miles traveled (VMT), as well as indications of increased congestion. Overall, there is a 42% increase in overall fuel consumed for this case due to some efficiency gains facilitated by the CAVs systems, but this is more than offset by the increased VMT.
- Highlighted results from a case study based in Bloomington, Illinois investigating privately owned vehicles with both partial automation (no zero-occupancy vehicle (ZOV) travel) and full automation (with ZOV travel) indicate that at the regional level ZOV trips could increase total automobile trips by an additional 27% (for low CAV penetration rates) and 39% (for high CAV penetration rates). In the worst-case, additional travel demand facilitated by full automation (both ZOV and new trips due to enhanced capabilities) could completely negate the beneficial impacts of VTO technologies on overall fuel usage over the next 30 years, leading to minimal reductions in national fuel usage.
- At the regional level, several promising mitigation strategies leveraging vehicle connectivity and automation were identified including: ZOV optimization, improved transit access, leveraging

connectivity and automation for improved situational awareness and control, large-scale traveler coordination, managed lanes (possibly including CACC specific lanes), and co-design of vehicle technology to incorporate the new functionalities associated with connectivity and automation. More specific information regarding these strategies and their impacts is provided in the next section (Section 3.4)

- A modeling investigation of CAV deployment and transition dynamics provided insights into the complex landscape of overlapping adoption, development, and regulatory phases CAV adoption faces, where different stakeholders can block or accelerate deployment. Examples include interactions between manufacturer R&D, VMT accumulation for insurance underwriting, time for regulatory approval, vehicle costs to consumers and achieving economies of scale. The study also investigated influential factors for CAV adoption and energy consumption sensitivities including strong influencers such as consumer preference, time valuation and technology costs; others include vehicle powertrain types and fuel economy, proportion of time freed by a particular CAV concept, willingness to pool, road congestion, and amount of deadheading (i.e., extra travel performed by ride-hailing vehicles in between passenger-carrying trips).
- As a means to estimate national level impacts of CAV technologies from detailed regional-level simulations, extrapolating the results of detailed, activity-based, transportation system simulations to other areas or other populations was found to be challenging. Extrapolating results was especially challenging for travel metrics such as VMT, since VMT depends not only on traveler characteristics, but also on road network characteristics and other land use characteristics at local and regional geographic scales.

3.3.1 Corridor Level Impacts of Connectivity and Automation

- In a freeway corridor, traffic throughput decreases and energy consumption increases as ACC market penetration increases. However, it is the opposite for CACC: Traffic throughput increases and energy consumption decreases as CACC market penetration increases. In other words, there is significantly more energy consumption for ACC than CACC at the same level of market penetration, and 100% CACC market penetration could completely remove traffic congestion at the current demand level, for the corridor simulated in this work.
- Active Traffic Management (ATM) strategies for freeways including Local Responsive Ramp Metering (LRRM), Coordinated Ramp Metering (CRM), Variable Speed Limit/Advisory (VSL/VSA) and the combination of CRM and VSA, have been simulated for SR-99 North Bound Corridor. The performance analysis included: total delays, average traffic speed, the number of lane changes (indication of traffic disturbances), fuel economy (MPG), and emissions (NOx, CO, CO2, HC, and PM2.5). For LRRM, Total Delay is reduced by 9%, and improvements in all other aspects are 1~2% over the baseline traffic. As for the improvements by CRM, VSA, and the combined CRM and VSA, the Total Delay reduction is five times more and other improvements are ten times more compared to those of the LRRM over the baseline traffic. CRM only worked slightly better than VSA alone, and the combination of CRM and VSA did not bring extra benefit.

CAV systems exist today only in very limited numbers of prototype vehicles with limited capabilities, so it is not possible to observe their impact on freeway corridor traffic. Consequently, it is necessary to depend on large-scale use of simulations to predict what would happen when CAV systems are deployed in large numbers. To this end, the CAV Pillar developed and applied traffic microsimulation tools to predict the impacts that CAV systems are likely to have on traffic and energy consumption, with minimal efforts at additional energy-centric controls (see Section 3.4 for more information on these strategies). Producing realistic estimates of the impacts is challenging, because they requires high-fidelity models that are sensitive to the changes in vehicle behaviors that will occur when they are equipped with CAV technology.

Note that this work does not directly optimize energy consumption, since it is not yet possible to formulate an objective function representing the total energy consumption for all the traffic in a freeway corridor. Therefore, for the corridor-level work in this section, energy consumption is indirectly optimized the throughput and indirectly reduce energy consumption. Using a microscopic traffic simulation of a freeway corridor with mixed traffic, the CAV Pillar analyzed several simulation scenarios. Mobility and energy consumption have been evaluated with individual trajectories saved from microscopic traffic simulation:

- Traffic throughput and fuel consumption impact of varying market penetrations of ACC and CACC on freeway corridor traffic
- Fuel consumption changes with changes in the market penetration of CACC vehicles
- The impact of ramp metering on mixed traffic (with manually driven vehicles and CAVs) throughput

3.3.1.1 Simulation of Mixed Traffic for Freeway

- In a freeway corridor, traffic throughput decreases and energy consumption increases as the ACC market penetration level increases. With 100% ACC market penetration, fuel consumption could increase by up to 60%.
- In the case of CACC, lower market penetration (<40%) increases the average energy consumption, as with ACC. but higher market penetration (≥40%) reduces the average energy consumption and increases throughput. At 40% CACC market penetration, fuel consumption begins to drop and continues to decline as market penetration levels rise. At 100% CACC market penetration, energy consumption could drop by up to 20%. In this study, with 100% CACC penetration, traffic congestion could be completely removed at the current demand level.
- Therefore ACC leads to significantly more energy consumption than CACC at the same market penetration. At 100% market penetration for both, ACC vehicles consume roughly 80% more fuel than CACC vehicles.

Early simulation studies by the SMART Consortium concentrated on freeway applications and were based on models of the vehicle-following performance of ACC and CACC systems for cars and heavy trucks. Although ACC and CACC systems represent Level 1 automation, their car-following behaviors are expected to be similar to the car-following behavior expected from vehicles with higher levels of automation, so these results can, to some degree, be generalized to those higher automation levels. One important distinction is between “autonomous” automation systems (which do not actively coordinate with other road-users) and cooperative automation systems (which use V2V communication to actively coordinate their behaviors).

To compare the impact of ACC and CACC penetration levels on traffic, the same calibrated baseline traffic was used for both ACC and CACC car-following models. Note that in a CACC string, the lead vehicle will always be in ACC mode when following a manually driven vehicle or another CACC string. For the latter case, the two CACC strings may combine if the total length does not go over the maximum CACC string length limit. Car-following behaviors used in this study were calibrated with field-collected data for a few ACC and CACC vehicles driven in public traffic. These car-following models are intended to capture the dynamic interactions between manually driven vehicles and ACC and CACC vehicles.

Figure 3-56 and Figure 3-57 show the contrast between the trends in achievable throughput per lane as the market penetration increases for ACC (unconnected) and CACC systems, respectively. The simulation scenario for these results was a section of four-lane freeway operating at its maximum achievable upstream throughput level, with a single exit ramp serving different exiting traffic volumes, ranging from none (the ideal case) to 25% of the mainline volume. The decline in achievable downstream throughput with increasing use of ACC is in distinct contrast to the increase in downstream throughput with increasing use of CACC. This occurs because ACC destabilizes the vehicle-following control, while the CACC stabilizes it and enables the vehicles to be driven at shorter gaps.

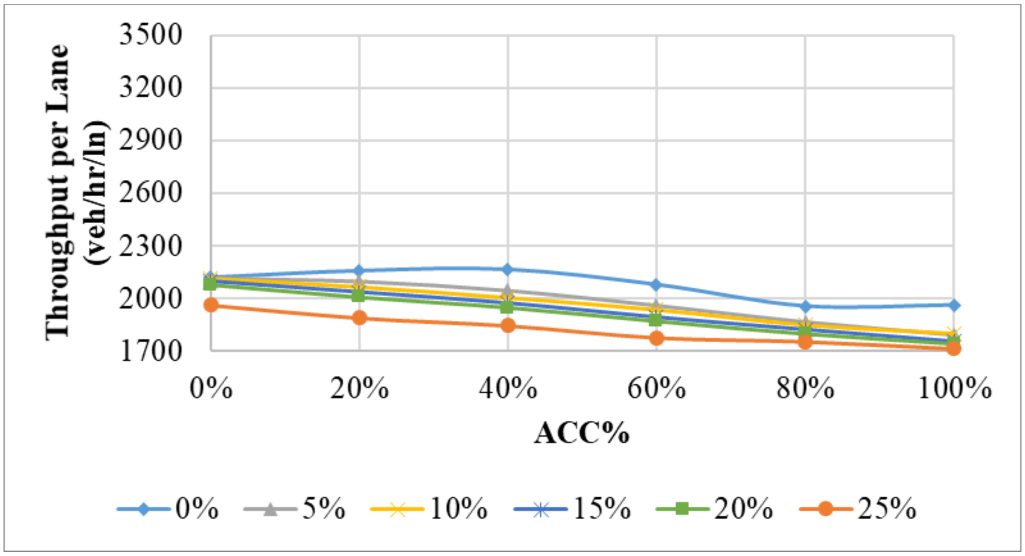


Figure 3-56. Corridor throughput versus ACC penetration level; the color codes represent the percent of flow through the exit ramp.

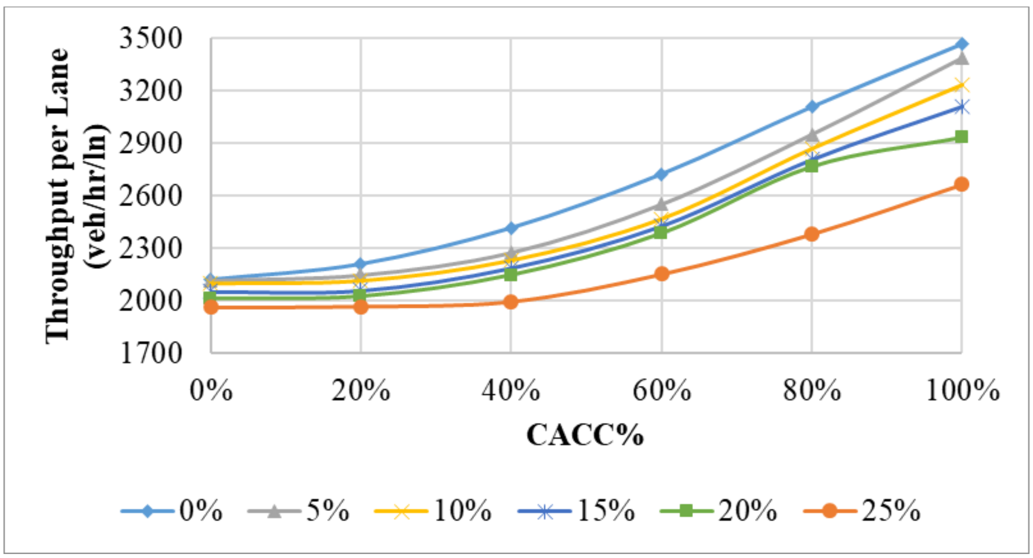


Figure 3-57. Corridor throughput with CACC penetration; the color codes represent the percent of flow through the exit ramp.

The effects of ACC and CACC on energy consumption can be visualized more clearly on contour plots for a simple scenario of a four-lane freeway section with a single on-ramp. Figure 3-58 shows a fuel consumption contour plot for a 13.5 km corridor for one hour of operation, with an upstream mainline approaching traffic flow of 1,950 vehicles/lane/hour, approximately the maximum capacity for manual driving, plus an on-ramp volume of 600 vehicles per hour beginning after the first 20 minutes of simulation. The vertical axis of each plot represents the location along the freeway, the horizontal scale represents the time, and the colors represent the traffic speeds. The results in Figure 3-58 also show that when all the vehicles are using CACC the impact of the on-ramp traffic is negligible, but that when all the vehicles are using autonomous ACC, the fuel consumption increases significantly because of the unstable vehicle-following behavior.

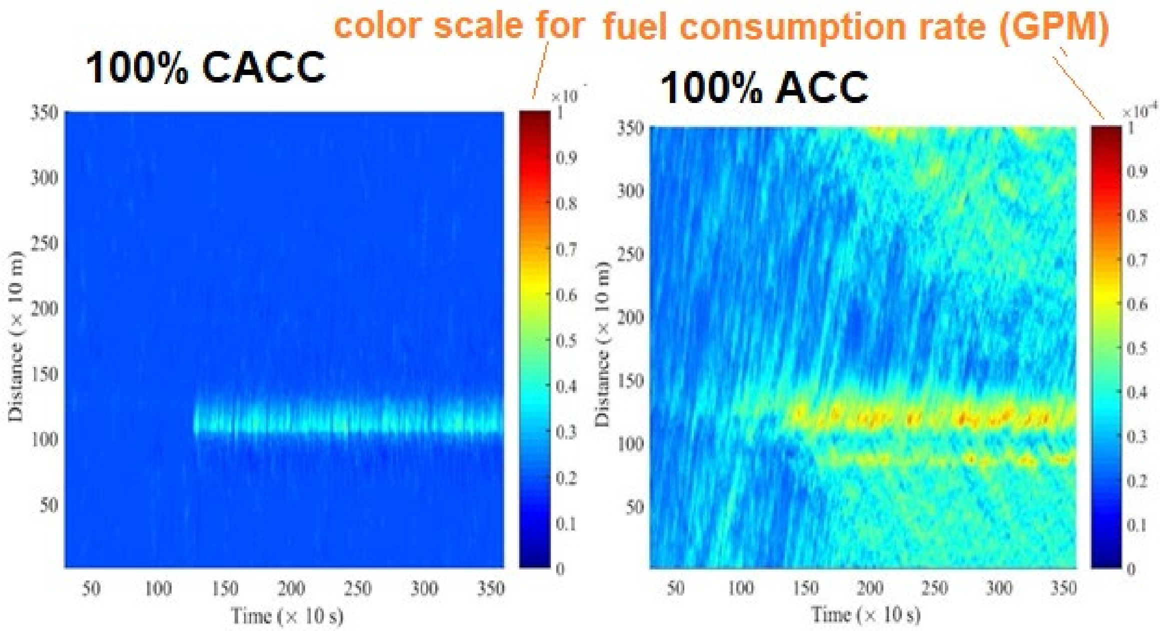


Figure 3-58. Fuel consumption rate (GPM - gallon per mile travelled) contour plot for 100% CACC driving (left) and 100% ACC driving (right) in response to a traffic disturbance caused by an on-ramp. The upstream mainline approaching traffic flow is 1,950 vehicles/lane/hour, and the on-ramp volume is 600 vehicles per hour.

Using the same freeway section simulation scenario — mainline demand of 1,950 vehicles/lane/hour and on-ramp demand of 600 vehicles per hour — Figure 3-59 and Figure 3-60 show how energy consumption changes with changing market penetrations levels of ACC and CACC in mixed traffic, respectively. Note that in CACC operation, the leader vehicle will usually operate in ACC mode, even in a single vehicle situation. At 100% market penetration of CACC vehicles, energy consumption could drop by approximately 7% to 20%, and the average (over time) energy consumption could drop by 15%. Therefore the same market penetration of ACC leads to significantly more energy consumption than CACC. Up to about 80% more energy is consumed with ACC than with CACC with 100% market penetration for both.

It can also be observed from Figure 3-59 that for combined mainline and the on-ramp traffic, (a) higher market penetration levels of ACC vehicles in mixed traffic (with manually driven vehicles and ACC vehicles) increase energy consumption, and (b) with 100% market penetration of ACC, energy consumption could increase by up to 60% over the baseline (current traffic with manually driven vehicles only). These results are in line with other predictions about the impact of ACC market penetration levels on mobility: Higher market penetration levels of ACC vehicles will reduce the flow of mixed traffic significantly.[114]

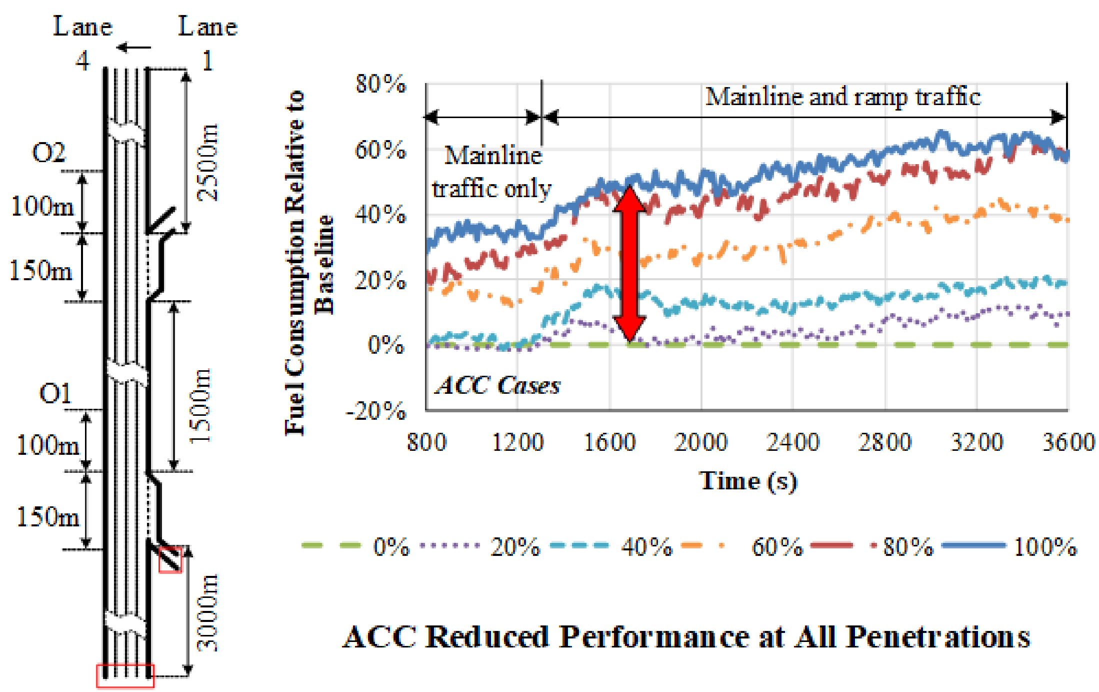


Figure 3-59. Energy consumption changes compared to the baseline traffic (manually driven vehicle only) with changes in market penetration levels of ACC vehicles.

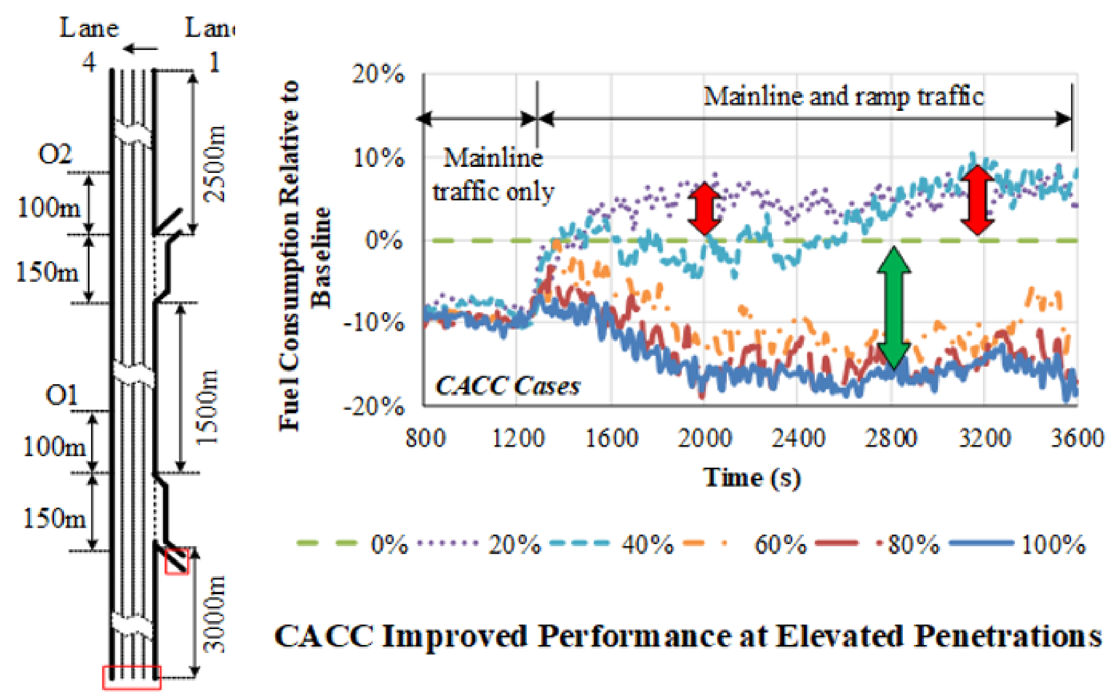


Figure 3-60. Energy consumption changes compared to the baseline traffic (manually driven vehicle only) with changes in the market penetration levels of CACC vehicles.

Figure 3-60 shows that for the combined mainline and on-ramp traffic (*t*>~1300s) (a) at low market penetration levels (<40%) of CACC, the average energy consumption over time will increase compared to the baseline (current traffic with manually driven vehicles only) since most vehicles have to operate in ACC mode due to limited opportunities to form platoons, (b) at market penetration levels of 60% and above, the average energy consumption starts to drop, and (c) at 100% CACC market penetration, energy consumption over time could drop between 7% and 20%.

For mainline traffic only (t<~1300s), even a 20% market penetration of CACC immediately leads to a 10% benefit (Figure 3-60). However, this is not the case for ACC only (Figure 3-59). When there is no on-ramp traffic, the performance of the 20% CACC case (with 5% effectively in string operation) is better than the baseline human driver case and the 20% ACC case, because the CACC string operation provides mobility and energy benefits to the traffic flow. In the ACC case, on the other hand, a minor random disturbance caused by lane changes could be amplified by the ACC controller, thus decreasing the stability of the mainline traffic flow.

At the on-ramp bottleneck, the on-ramp traffic would disrupt the CACC string operation in the freeway mainline. For the 20% CACC case, as the mainline strings are broken, those CACC vehicles switch to the ACC mode, making the scenario performance similar to the performance observed at the 20% ACC case. When the CACC market penetration gets higher, most of the on-ramp vehicles are CACC vehicles themselves. They can join the mainline CACC string after merging into the freeway traffic. In this case, the disturbance from the ramp traffic becomes smaller and the freeway performance at the on-ramp bottleneck starts to improve.

Another finding from examining the four-lane freeway section is that there may be a subtle trade-off between fuel consumption and maximum freeway throughput at higher traffic volumes. When the use of CACC is maximized, and traffic throughput is pushed to the maximum achievable by operating long strings of CACC vehicles, congestion can re-emerge as the highway is handling a much higher traffic volume. This trade-off is shown in Figure 3-61, which shows (for CACC vehicles) the downstream capacity of a freeway section increasing as the upstream input traffic increases, but with some flattening as congestion builds up (red curve), while the energy efficiency declines (as calculated by MOVES and VT-Micro based on simulated individual vehicle trajectories) as that congestion increases (blue curve). Note that the vertical scale on the right side of the plot shows energy savings toward the upper end (negative signs in fuel consumption signifying savings).

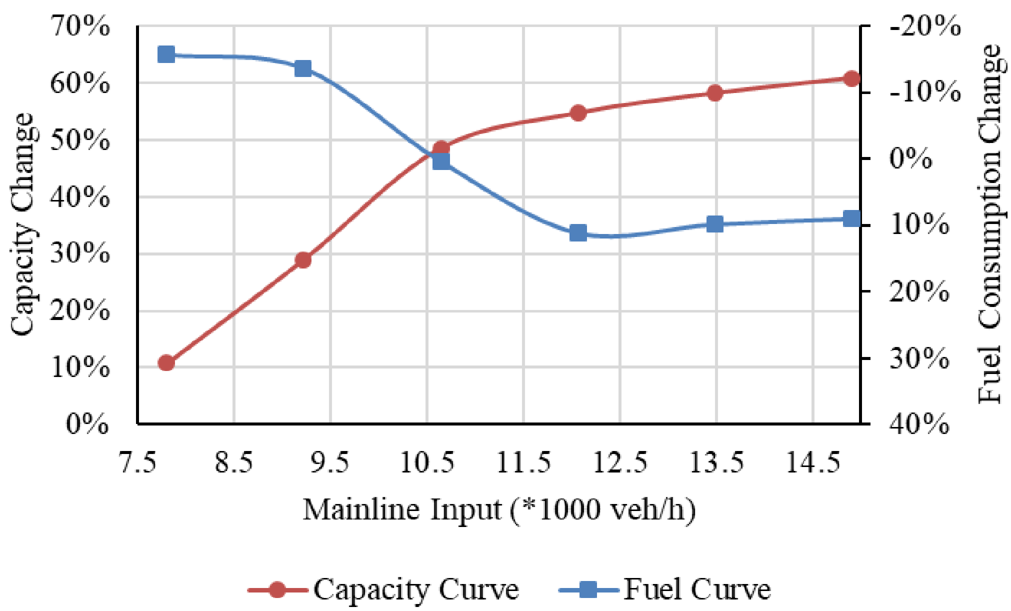


Figure 3-61. For a freeway section: trends in downstream freeway lane throughput and energy efficiency as traffic volume increases with 100% CACC penetration.

The calibrated models of ACC and CACC vehicle-following were also applied to real-world freeway corridors. The initial calibration of the human driver model parameters was done for the SR-99 freeway corridor approaching Sacramento, CA, from the south during the morning peak period. The upper left corner of Figure 3-62 shows the contour plots of traffic speeds along this corridor in the current base case (no CACC vehicles), followed by plots showing successively larger market penetrations of CACC, from 20% to 100% in 20% increments. The vertical axis of each plot represents the location along the corridor, the horizontal scale represents the time from 4:00 a.m. to 12:00 noon on a weekday, and the colors represent the traffic speeds.

While there are many on-ramps and off-ramps along this section of the corridor, there are three major bottlenecks, which are noted in the top of Figure 3-62.. As the CACC market penetration increases, the bottlenecks can be seen to dissipate, while the corridor traffic volume remains the same as in the base case. This demonstrates the ability of CACC to reduce the traffic congestion that produces inefficient use of energy. Note that the 20% market penetration is actually worse than the base case. This occurs because the CACC system reverts to ACC when there is not a CACC-equipped vehicle in front of it, and at this low market penetration level most of the CACC vehicles have not arrived right behind another CACC-equipped vehicle, so they have been compelled to function in ACC driving mode.

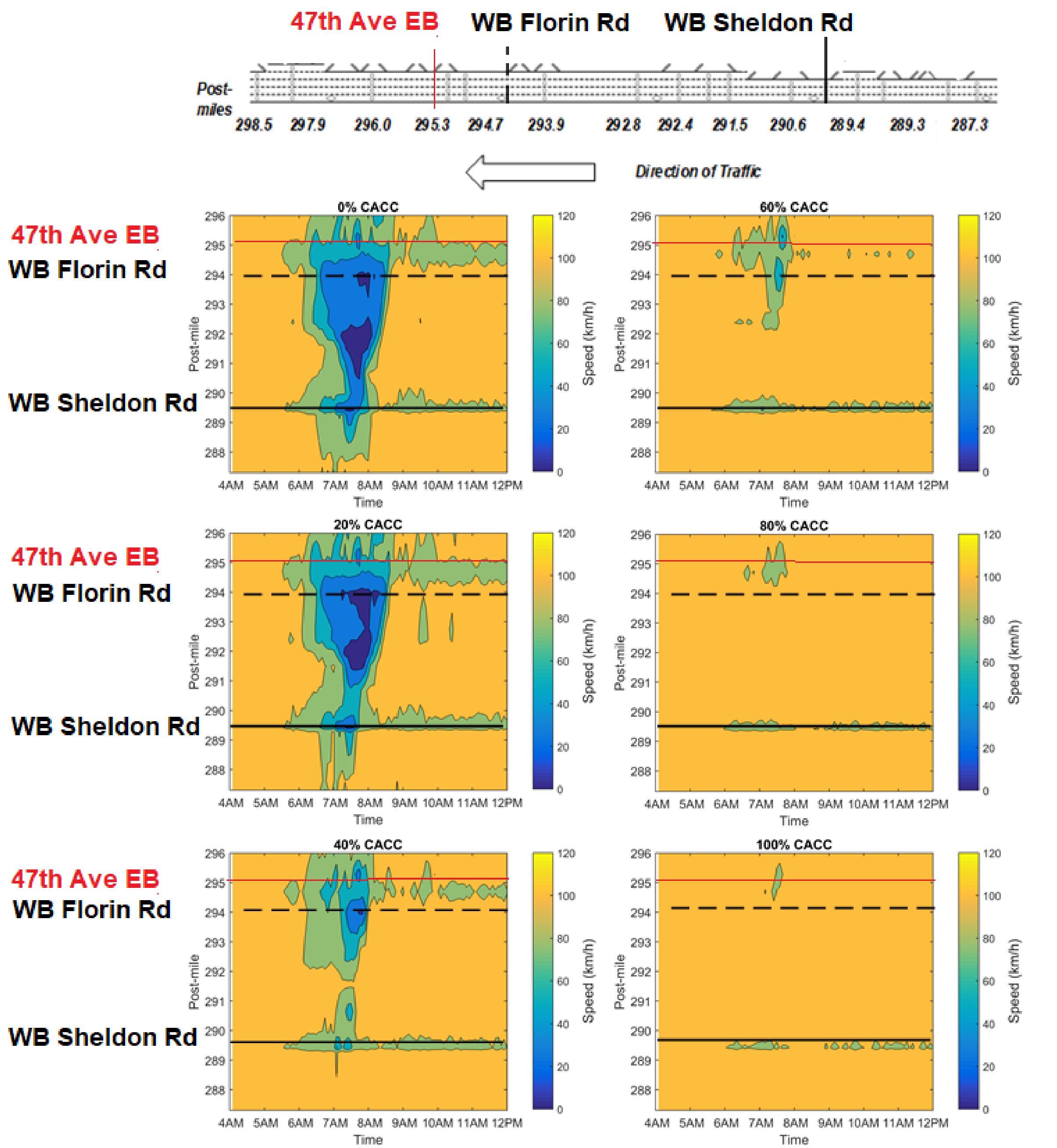


Figure 3-62. Speed contour plots for SR-99 Sacramento corridor with all-manual driving and CACC at market penetrations from 20% to 100%. The horizontal lines in the speed contour plots indicate the locations of the three on-ramps, based on postmile, which are the major bottlenecks along the corridor for peak morning traffic. The road sketch and traffic direction is depicted on the top.

3.3.1.2 Energy and Emissions Evaluation of Ramp Metering in Microscopic Mixed Traffic Simulation

- For a simple freeway section with a merge bottleneck at a single on-ramp, ramp metering can improve mobility via increased throughput as well as reduce energy consumption and emissions. This improvement in average fuel consumption and emissions can be as high as 20% at high on-ramp demands (1200 veh/hr to 1500 veh/hr).

- In addition to the simple freeway section, several Active Traffic Management (ATM) strategies were implemented and simulated on a realistic corridor (SR-99 North in California) to analyze their impact on traffic flow, energy consumption, and emissions. Compared to the baseline case with no metering on the simulated corridor, Local Responsive Ramp Metering (LRRM) was found to provide 2-9% traffic flow and 1-2% emissions and fuel economy improvements. Coordinated Ramp Metering (CRM) and Variable Speed Advisory (VSA) strategies both achieved over a 20% improvement in mobility, emissions, and fuel savings, with CRM-alone working slightly better than VSA alone. The combination of both CRM and VSA did not show additional benefits for simulations done within this work.

Ramp metering is one traffic management strategy for controlling the flow from an on-ramp onto a freeway. Unmetered high-volume entrance traffic can significantly affect mainline traffic flow and create bottlenecks at the on-ramp merge area. Ramp metering can often help relieve these bottlenecks. There are different implementations of ramp metering and it is the subject of significant continued research. Time-of-day fixed metering rates (where the rate is determined by the time of day regardless of the traffic situation) are used in many states in the U.S. In California, almost all Caltrans freeways use LRRM, which determines the metering rate based on the real-time occupancy measurement immediately upstream of the on-ramp, using a look-up table that provides the suggested ramp metering rate for the corresponding threshold of occupancy levels. In contrast to LRRM, Coordinated Ramp Metering (CRM) intends to optimize the traffic throughput in a corridor by managing traffic from a system-level viewpoint and determining the ramp metering rates jointly for all on-ramps along a freeway corridor. The CRM algorithm implemented for this work to evaluate energy impacts was developed in previous work[115,116] and uses a Model Predictive Control approach to optimize the trade-off of Total Travel Time and Total Travel Distance based on field available traffic detections.

While ramp metering controls the traffic demand into the freeway, once the vehicles get onto the freeway they are no longer controlled by the ramp metering, and traffic patterns are determined by driver behavior. To control or affect the mainline traffic directly, a Variable Speed Limit or Advisory (VSL/VSA) strategy is necessary. VSL and VSA are effectively the same control method with the only difference being that VSL is legally compulsory and VSA is advisory. Therefore, with a VSA strategy a driver can still choose to comply with the advisory or not. Obviously, higher levels of driver compliance will likely generate better control effects. For vehicles with longitudinal automation and I2V connectivity, the VSL/VSA information can be directly used on the vehicles as the set-speed for longitudinal control. In this sense, a CAV can be used as a traffic regulator due to its positive impact on the overall traffic.[117] The VSL/VSA algorithm implemented for this work uses an algorithm developed and field tested along the SR-78 East Bound Corridor near Escondido, San Diego.[118,119] The driver compliance rate used in the simulation was the rate of observed in-field compliance during the SR-78 testing as indicated by radar-based detection near all roadside VSA signs. While the previous efforts discussed above did not consider the energy and emissions impacts of the developed VSA strategy, this work evaluates the impact mobility impacts as well as the energy consumption and emissions impacts of the discussed traffic management strategies for freeway traffic.

The road geometries considered were (a) a simple freeway section with a merge bottleneck at a single on-ramp, and (b) a real-world freeway corridor, northbound SR-99, with multiple on-ramps and off-ramps. The purpose of studying a simplified freeway section is that the system can be isolated from the effects of its upstream in-flow and downstream back propagation. Since ramp metering controls the demand from the on-ramp, which affects the on-ramp queue and the total travel time, both the mainline and on-ramps have been evaluated rather than the mainline only.

Evaluating the impact of mixed traffic with CAVs and manually driven vehicles on energy consumption and emissions with microscopic traffic simulation is a challenging task because of the need to consider inputs and interactions at three different levels:

1. Individual vehicle
2. Mesoscopic traffic, such as a freeway or an arterial corridor with aggregated traffic data and the corresponding energy and emission models
3. Macroscopic traffic, such as a city or a region with highly aggregated data and the corresponding evaluation models

These efforts used several energy consumption models, including MOVES[120,121,122], Autonomie[123], and the VT-CPFM.[124]. It was discovered that each model has its own pros and cons, and they all need experimental data for calibration for a reasonably accurate energy consumption evaluation. For example, MOVES can only be used with aggregated data. Autonomie can be used for individual vehicles, but it depends on the vehicle type and other powertrain characteristics, requiring an estimate of the individual vehicles and types operating in the evaluation environment. In addition, using Autonomie with microscopic traffic simulation requires extremely high computational power, since each vehicle requires a corresponding dynamic vehicle-level model and feedback control. The CAV Pillar developed a creative way to use Autonomie for energy consumption evaluation by using a randomly selected small percentage (e.g., 10%) of vehicles in a microscopic traffic simulation for the overall energy consumption evaluation. This method can still achieve reasonably accurate results compared to using all of the individual vehicle trajectories (speed, acceleration/deceleration, etc.) from a given microsimulation.

Autonomie was developed for individual vehicle modeling and feedback control development, and energy consumption and emission estimation. However, using Autonomie for energy consumption and emission estimation of the traffic along an entire freeway corridor, which includes thousands of vehicles, would not be possible due to computation overhead. To use Autonomie for energy consumption and emission estimation in a microscopic mixed traffic simulation at an aggregated level, 10% of the vehicle trajectories were randomly selected as the representatives and saved to feed into Autonomie for calculation. Average fuel consumption and emissions metrics were measured on a per-kilometer and per-vehicle basis in order to account for the fact that different scenarios have different number of vehicles simulated (due to varying on-ramp demand) and that vehicles travel varying distances.[125]

This work first considered the effect of time-of-day fixed rate metering on a simple freeway section, as shown in Figure 3-63:

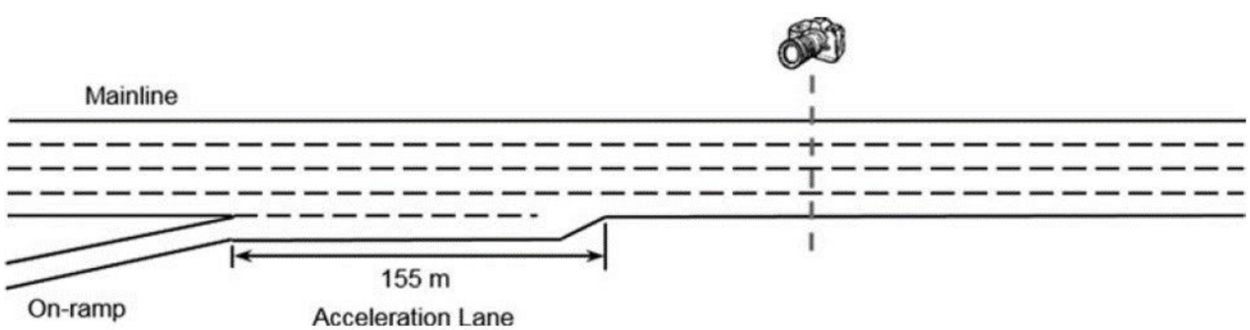
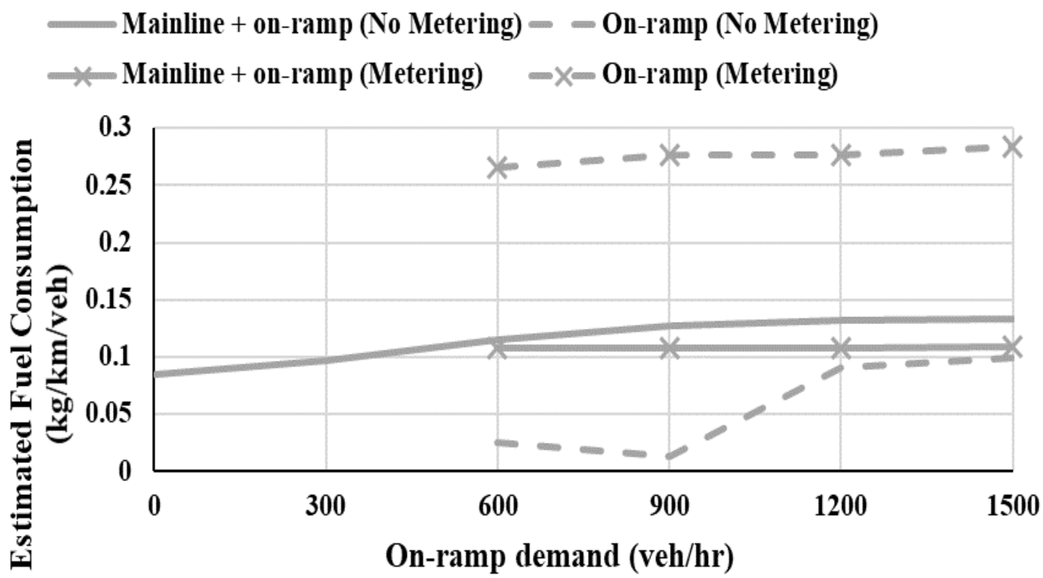
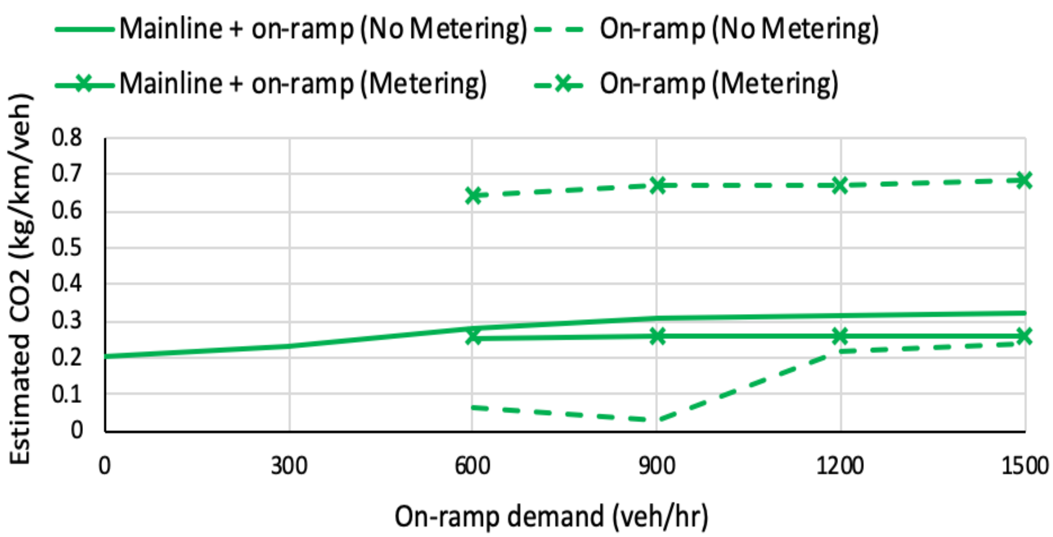


Figure 3-63. Simple freeway section with a merge bottleneck at the one on-ramp

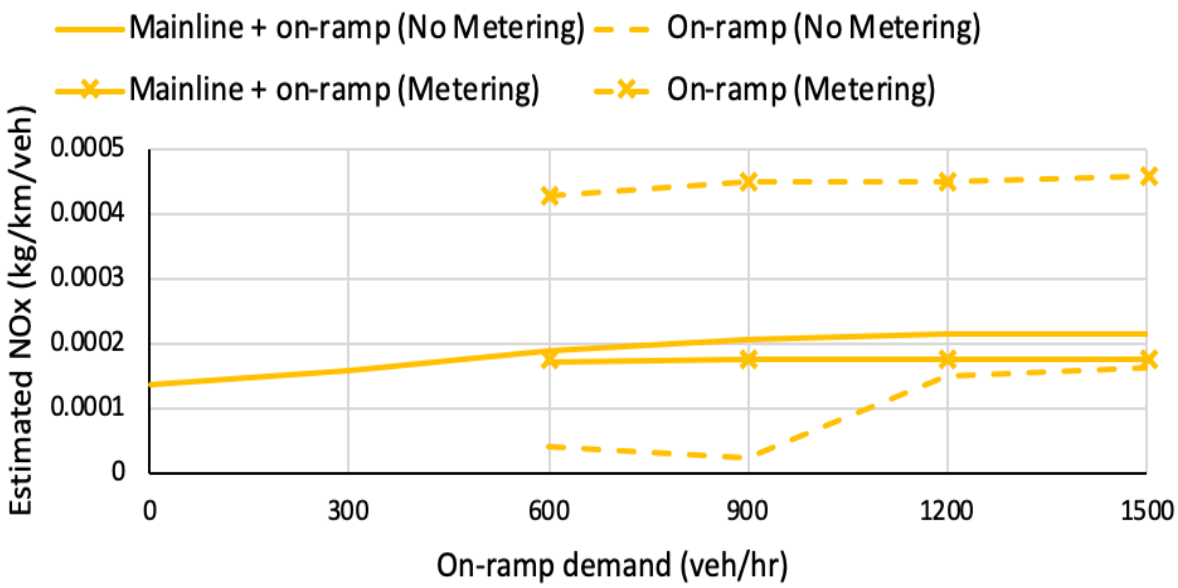
In Figure 3-64, the solid lines represent the fuel consumption or emissions estimates for the freeway merge (mainline and on-ramp combined), while the dotted lines represent fuel consumption and emissions estimates at the on-ramp only. Before implementing a fixed rate ramp metering strategy, which controls the demand onto the freeway from the on-ramp by adjusting the metering rate (or entrance flow), the average fuel consumption and emissions increased at a constant rate as the on-ramp demand increased from 300 veh/hr to 900 veh/hr. After implementing ramp metering at a fixed rate of 400 veh/hr, the average fuel consumption and emissions still increase, but at a slightly lower rate. This indicates that there is a correlation between capacity drop due to higher on-ramp demands and increased average fuel consumption and emissions; capacity drop due to high on-ramp demand can lead to as much as 57% more fuel consumption and emissions per kilometer for each vehicle, compared with the case where the on-ramp demand is absent (Figure 3-64).[126] Fuel consumption (kg/km/veh.) and emissions (CO, PM2.5, NOx, CH4 (kg/km/veh.)). have been analyzed with Autonomie based on simulated trajectory data, as shown in Figure 3-64.



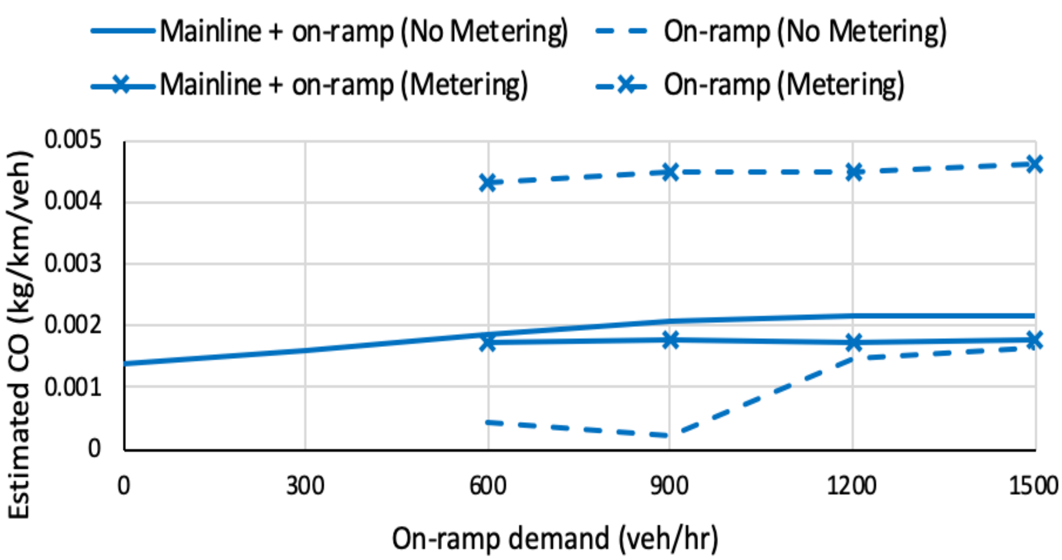
(a) Fuel consumption



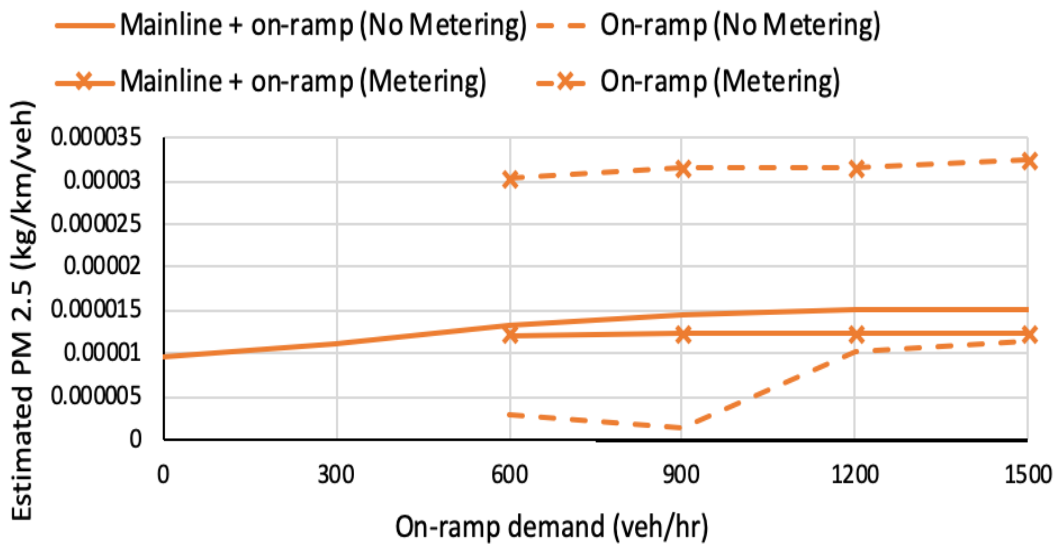
(b) CO2


Mainline + on-ramp (No Metering)
On-ramp (No Metering)
Mainline + on-ramp (Metering)
On-ramp (Metering)
Estimated NOx (kg/km/veh)
0.0005
0.0004
0.0003
0.0002
0.0001
0
0
300
600
900
1200
1500
On-ramp demand (veh/hr)

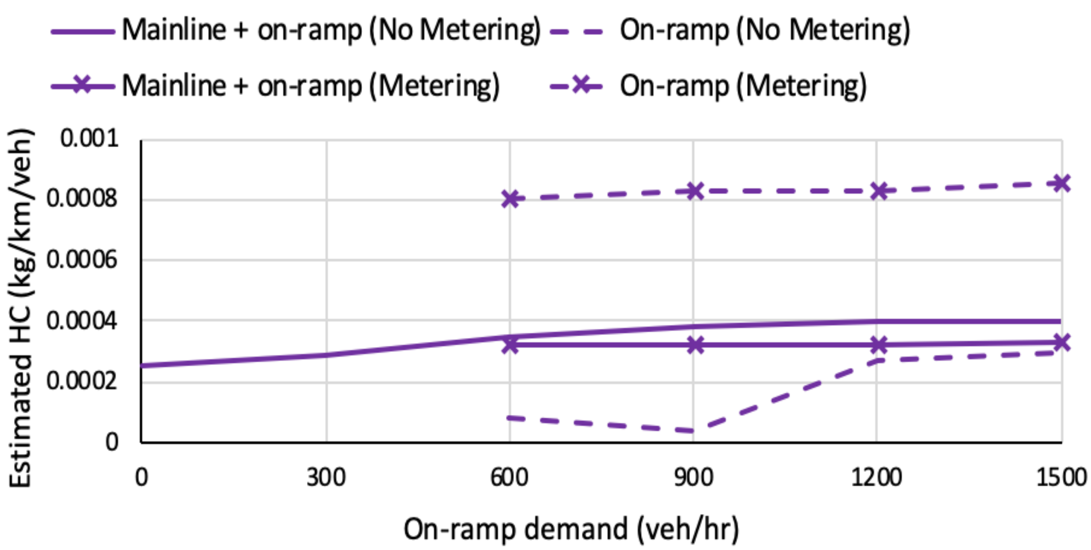
(c) NOx


Mainline + on-ramp (No Metering)
On-ramp (No Metering)
Mainline + on-ramp (Metering)
On-ramp (Metering)
Estimated CO (kg/km/veh)
0.005
0.004
0.003
0.002
0.001
0
0
300
600
900
1200
1500
On-ramp demand (veh/hr)

(d) CO



(e) PM 2.5



(f) HC

Figure 3-64. Emission and fuel consumption estimates at varying levels of on-ramp demand with fixed metering rate of 400 veh/hr.

As shown in Figure 3-64 once the on-ramp was metered at a fixed rate of 400 veh/hr for on-ramp demands of 600 veh/hr or higher, the average fuel consumption and emissions on the mainline are no longer as high as those observed without ramp metering. Note that the plot only shows emissions in relation to on-ramp demand, not metering rate. The ramp meter rate is not shown.

This improvement in average fuel consumption and emissions can be as high as 20% at high on-ramp demands (1200 veh/hr to 1500 veh/hr). This can be attributed to higher overall freeway merge capacity, leading to lower delay and less travel time. In addition, careful inspection of Figure 3-64 reveals an interesting finding:

Metering the on-ramp when the on-ramp demand is 600 veh/hr or higher restricted the on-ramp flow and caused the average fuel consumption and emissions to increase significantly, and this is also correlated to the significant increase in the stop time and total number of stops on the on-ramp shown in Table 3-6. However, although ramp metering increased the number of stops and stop time on the on-ramp, it led to higher freeway merge capacity, fewer stops and less stop time on the mainline, which contributed to an overall reduction in average fuel consumption and emissions. This phenomenon is very similar to the observation that ramp metering improves the overall capacity of the freeway merge at the expense of restricting the flow and increasing the delay of the on-ramp.

Table 3-6. Comparison of stop time and number of stops on mainline vs on-ramp metered at 400 veh/hr.

On-ramp demand (veh/hr)	No Metering				Metering			
	600	900	1200	1500	600	900	1200	1500
Stop time (sec)								
Mainline	0.04	4.11	10.56	11.25	0	0	0	0
On-ramp	0	0.95	59.41	67.9	437.98	498.01	500.76	506.27
Number of stops (#/veh)								
Mainline	0	0.11	0.21	0.22	0	0	0	0
On-ramp	0	0.11	0.62	0.67	1	1	1	1

Although even a simple ramp metering strategy like the time-of-day fixed metering rate control was shown to improve energy consumption for a simplified freeway section with a downstream bottleneck, similar results for the same metering strategy applied to a freeway corridor with complicated traffic patterns are unlikely. For complex traffic scenarios, a given section of a freeway corridor is affected by its upstream and downstream traffic. Such two-directional chain effects would not be comprehended in an isolated freeway section as discussed above. Therefore, the simulation of traffic along a freeway corridor is absolutely necessary to analyze realistic traffic impacts. For this reason, several ATM strategy were simulated for California's SR-99 North Bound Corridor. The ATM strategies implemented and simulated include: LRRM, CRM, VSA, and the combination of CRM and VSA. The simulated performance analysis includes: total delays, average traffic speed, the number of lane changes (indication of traffic disturbances), fuel economy (MPG), and emissions (NOx, CO, CO_2, HC, and PM2.5). It is noted that the simulations have only been conducted for status quo traffic (manually driven vehicles) and do not include an automated vehicle behaviors at this stage. The energy and emissions have been evaluated with Autonomie developed Argonne National Laboratory. Sensitivity analysis with respect to the market penetration of CAVs in mixed traffic is an area for future research.

From Table 3-7 below, it can be observed that energy consumption and emissions have been improved over the baseline traffic for all of the various ATM strategies simulated for the corridor. This is the case even for LRRM; however, CRM and VSA achieved significantly larger improvements than LRRM in all aspects. This is because LRRM is a local approach, which only looks at the traffic detection of its immediate upstream section, not system wide. Therefore, LRRM is a selfish algorithm which can lead to issues and instabilities elsewhere in the system. In contrast, both CRM and VSA determine the ramp metering rates and the desired speeds from a system-level viewpoint, including mainline sections, on-ramps and off-ramps, optimizing overall traffic mobility. It should be noted that the energy consumption and emissions have not been directly considered as factors in the traffic optimization, rather their improvement is a byproduct of the improved traffic mobility.

Table 3-7. Emission and fuel consumption estimates (no metering vs. highlighted ATM strategies).

Ramp metering strategy	No Metering	LRRM	CRM	VSA	CRM+VSA
Fuel Economy (mpg)	31.39	1%	28%	27%	28%
NOx (kg/veh/mile)	1.95E-04	-2%	-24%	-22%	-22%
CO (kg/veh/mile)	1.96E-03	-2%	-23%	-21%	-22%
CO2 (kg/veh/mile)	0.291	-1%	-23%	-22%	-22%
HC (kg/veh/mile)	3.63E-04	-2%	-22%	-21%	-22%
PM 2.5 (kg/veh/mile)	1.37E-05	-1%	-23%	-21%	-22%

It can be observed from Table 3-8 that the total delay reduction enabled by the CRM, VSA and the combination strategies is about 5 times that of the LRRM reduction. For other aspects, the improvements are over 10 times more. This again indicates the merits of a system-level approach over a local approach. From these results, there is one question yet to be answered: since CRM and VSA should be complementary in function from a traffic management viewpoint; why does the combination of CRM & VSA not bring extra benefit compared to CRM and VSA alone? This question is recommended for future research.

Table 3-8. Mobility performance (no metering vs. highlighted ATM strategies).

Ramp metering strategy	No Metering	LRRM	CRM	VSA	CRM+VSA
Delay (sec/km)	31.69	-9%	-47%	-45%	-45%
Average speed (km/hr)	65.53	2%	14%	12%	13%
Number of lane changes (#/km)	1709.19	-1%	-13%	-13%	-13%

In summary, this section has preliminarily considered the effects of highlighted Active Traffic Management strategies in terms of their mobility, energy consumption and emissions impacts. The simple case considered was a fixed rate ramp metering strategy of 400 veh/hr which appeared to remove the mainline capacity drop at a bottleneck for an isolated freeway section with a downstream onramp bottleneck. However, this mainline improvement does not necessarily mean an improvement in overall mobility, since the onramp queue for the simple freeway section could be significantly large at high demand levels. Several other ATM strategies including LRRM, CRM, VSA and the combination of CRM and VSA were implemented for a more realistic and well-calibrated freeway corridor, SR-99 Northbound. The ATM strategies were developed for a direct mobility improvement, however, the simulation results also showed that energy savings and emission reductions could also be achieved as a byproduct of the improved mobility. Although LRRM provided some improvement to the traffic in all three aspects of interest: mobility, energy saving and emission reduction, CRM, VSA and combined CRM and VSA was found to provide significantly larger improvement compared to the LRRM implementation in all performance aspects. CRM worked slightly better than VSA alone, and the combination of CRM and VSA did not show an additional benefit when applied to the corridor simulated within this work.

Further research regarding ATM strategies should include a sensitivity analysis of the highlighted ATM strategies for mixed traffic with respect to different levels of connectivity and automated driving market penetrations. It would also be interesting to analyze the effect of combined CRM and VSA more deeply to understand why the combination of both strategies did not bring additional benefits compared to CRM or VSA alone although their functionality in freeway traffic control should be complementary.

3.3.2 Regional-Level Impacts of Connectivity and Automation

- The impacts of CAVs are highly dependent on the value of travel time (VOTT). A preliminary study based in Chicago showed that partially automated vehicles could cause up to 45% increase in VMT if VOTT is reduced by 50% at full market penetration, while VMT would only increase by 9% if no VOTT change is assumed.
- If vehicle technology improvement occurs along a business-as-usual (BAU) trajectory, there could be essentially no fuel use reduction (~6%), despite continued vehicle improvements, due to zero-occupancy vehicles (ZOVs) and high CAV accessory loads, driving additional VMT and reducing overall efficiency.
- ZOV trips for personally owned vehicles related to repositioning and other behaviors lead to a significant increase in overall travel, as these vehicles do not have the higher efficiencies associated with larger-scale ride-hailing shared automated vehicles (SAVs).

Extending the work done for vehicle-level and corridor-level analysis, the CAVs Pillar explored the impacts of connected and automated vehicles at a regional level. This is necessary because the way in which individual CAVs and small groups of CAVs function and interact with individual travel behavior, as well as larger scale transportation system operations, affects the transportation system as a whole. In order to anticipate possible impacts at the regional scale, the POLARIS agent-based transportation systems simulator was used to explore a variety of scenarios representing potential changes introduced by CAVs. The POLARIS simulator was adapted as discussed in 3.2.3 to represent these changes. The next several sub-sections discuss studies exploring the impact of automation levels and vehicle sharing strategies on regional energy and mobility.

3.3.2.1 Impact of CACC and Other Automation Technologies on Regional Traffic Flow, Mobility and Energy Use

- Partially automated vehicles could cause up to a 45% increase in VMT if VOTT is reduced by 50% at full market penetration, while VMT would only increase by 9% if no VOTT change is assumed.
- As VOTT is reduced, individuals living in downtown and other urban core areas are already near more optimal activity spaces and do not tend to engage in as much extra travel as others do.

While corridor-level microscopic simulations of CAVs in various modes of operation (e.g., isolated vehicles and CACC) are possible, their full impact can be only captured at the network level. However, most of the current state-of-the-practice mesoscopic and macroscopic simulation tools cannot accurately capture the impacts of CAVs on congestion, emissions, and travel time reliability. Using the updated regional level modeling capabilities discussed in Section3.2.3, several simulations were conducted for various market penetration rates of CAVs (considering both CACC and isolated automated vehicles (AVs).

Using the updated POLARIS activity-travel simulator, a set of cases regarding the potential impacts of privately owned partially automated (Level-4) CAV deployment were analyzed for the Chicago metropolitan area. In this work, "partially automated" refers to vehicles that are capable of limited self-driving but still require drivers in the vehicle. The incremental AV costs were modified from $0 to $15,000 to achieve the market penetration values specified in Figure 3-65. A range of value of travel time (VOTT) reduction due to CAV, and CAV technology purchase models developed within the SMART Consortium efforts[127], were applied to evaluate the results. The results show that CAVs have some congestion-relieving effects when no assumption of VOTT change is made (i.e., low rebound). However, as VOTT is reduced, travel increases occur. The worst case (50% reduction in VOTT) shows a 48% increase in vehicle hours traveled (VHT) and a 45% increase in vehicle miles traveled (VMT), as well as indications of increased congestion. Overall, there is a 42% increase in fuel consumption in the high CAV case.

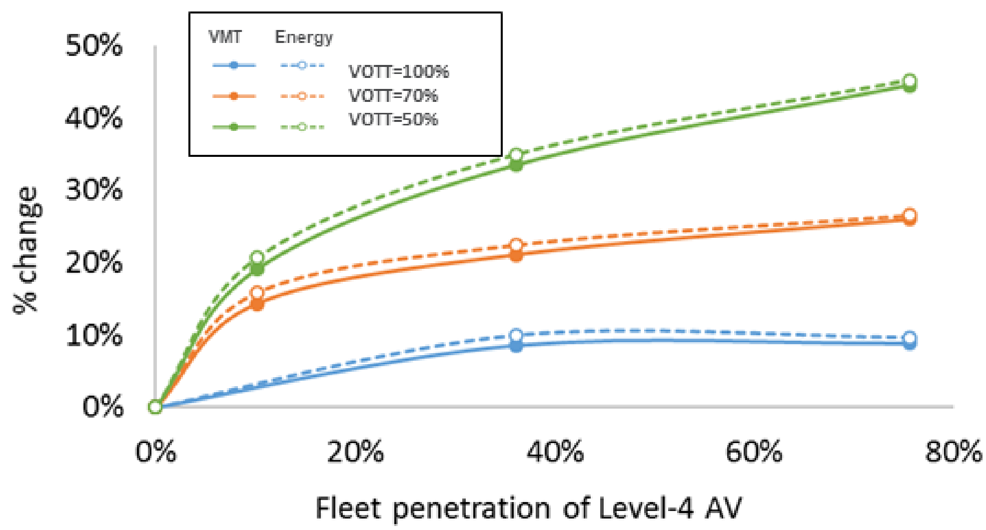


Figure 3-65. VMT and energy charge versus CAVs penetration and VOTT.

Figure 3-66 shows the geographic distribution of changes in fuel consumption for two cases using BAU year 2040 vehicle technologies. The results show that changing the cost of CAV ownership, while holding the VOTT fixed, results in substantial fuel increases in outlying and more wealthy areas of the region, while holding the cost fixed and varying the VOTT shows a fairly uniform increase in energy and travel across the region, as expected, with the exception of high density employment and activity areas. Individuals living in downtown and other urban core areas are already near optimal activity spaces and do not tend to engage in substantial amounts of extra travel regardless of the change in VOTT.

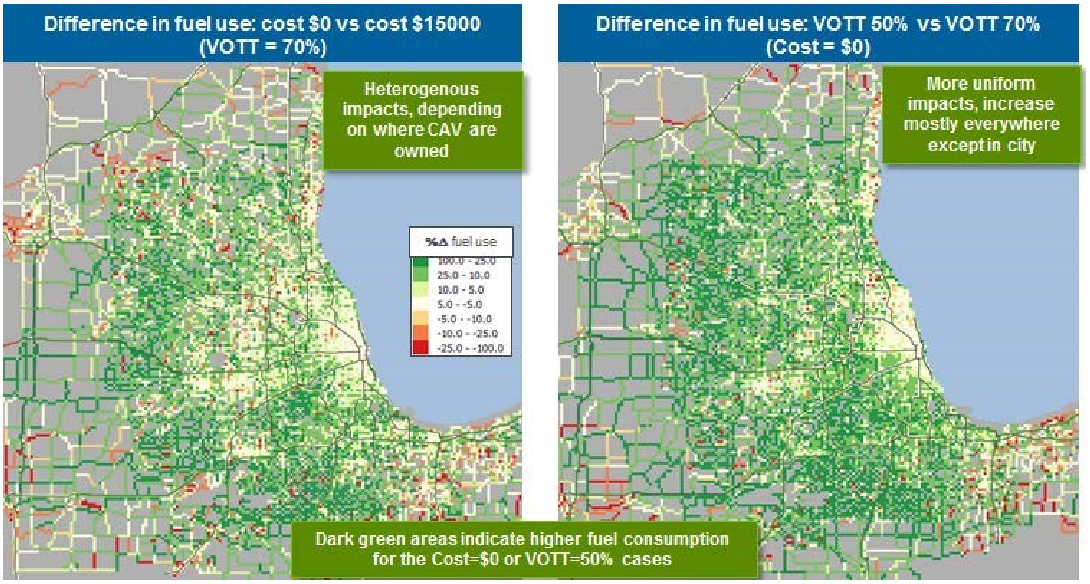


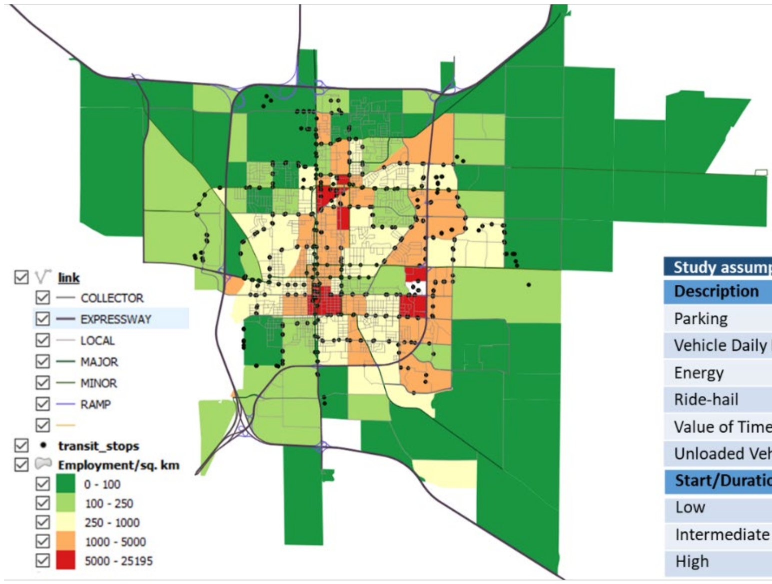
Figure 3-66. CAV scenario fuel use changes.

3.3.2.2 Large-Scale Regional Privately Owned CAV Level-5 (Fully Automated, Driverless Capable) Scenarios and Insights

- Many additional zero-occupancy vehicle trips are generated as privately owned CAVs are introduced and shared among household members — with total auto trips increasing by 39% in the worst case.
- If vehicle technology improvement occurs along a business-as-usual (BAU) trajectory, there could be essentially no fuel use reduction (~6%), despite continued vehicle improvements, due to ZOV and high CAV accessory loads.

One of the possible scenarios for the future of transportation/vehicle ownership is adoption of privately owned fully automated (Level 5) AVs. To model the travel behaviors of these households, an optimization model was developed that uses the household's travel plans and schedules, as well as transportation network information, as inputs and generates the AV's travel plans. The mixed integer programming (MIP) optimization model finds the optimal number of Level 5 AVs that a household needs, given its activities and schedules. The model also schedules the optimal AV trips, while considering vehicle sharing and carpooling between household members, travel to home/parking, flexibility in timing, taxis, and various travel costs, as well as any charges for zero-occupancy travel. The travel-related costs include energy, value of time, vehicle ownership, parking, and taxi/ride-hail trip fares for trips that cannot be satisfied by the household AV. The optimization model has been integrated with POLARIS and is called upon whenever a household is determined to have privately owned AVs. The results of the optimization model (encompassing the AVs' travel plans, including ZOV trips) are also simulated in the POLARIS traffic simulator.

A case study was conducted for Bloomington, Illinois, for the base year (2015), short-term view (2025), and long-term view (2040), with details shown in Figure 3-67. The demand assumptions included high CAV demand (with a marginal cost of $5,000, high activity scheduling flexibility) and low CAV demand (with a marginal cost of $15,000, low flexibility) The value of travel time is 50% of base in both cases, which is approximately similar to the VOTT difference between driving and traveling on high-quality transit. Data on the base- and forecast-year land use, population, and employment were provided by the Bloomington Metropolitan Planning Organization (MPO), and vehicle distributions were obtained from Polk/IHS Markit registration data for the base year. Both CAVs with partial automation and no ZOV travel capabilities and full automation with ZOV travel were considered in the scenarios.



Model characteristics:
- Agents:
  - 65,000 households
  - 156,000 people
  - 680,000 trips
  - 923 transit vehicle trips
- Physical systems:
  - 222 TAZs
  - 2,833 activity locations
  - 3,947 links
  - 470 transit stops

Study assumptions	
Description	**Cost**
Parking	$0/hr
Vehicle Daily Fixed Cost	$20/veh
Energy	$0.13/mile
Ride-hail	$3 + $0.8/mile
Value of Time	$10/hr
Unloaded Vehicle Pricing	0 , $0.33/mile
Start/Duration Flexibilities (minutes)	
Low	5
Intermediate	15
High	60

Figure 3-67. Scenario design for Bloomington case studies.

A summary of the case study assumptions and results is provided in the Appendix, and primary results are summarized below in Figure 3-68. Highlighted conclusions from the Level 5 cases suggest that ZOV trips could increase total automobile trips by 27% (for low CAV penetration rates) and 39% (for high CAV penetration rates) over the baseline, whereas introducing ZOV pricing of $0.33 per mile could reduce the impact to some degree (down to 25% and 35%, respectively, for the low and high rates). Fuel consumption is reduced by up to 75% for low CAV penetration and by up to 71% for high CAV penetration rates, depending on the CAV accessory load for the high technology improvement case. However, in the low-tech cases, fuel reductions can be as low as 6% from baseline (essentially no change from current fuel use despite vehicle powertrain advances). The case studies also found that ZOV pricing could further reduce fuel consumption by 1% and 5%, depending on vehicle technology and CAV penetration.

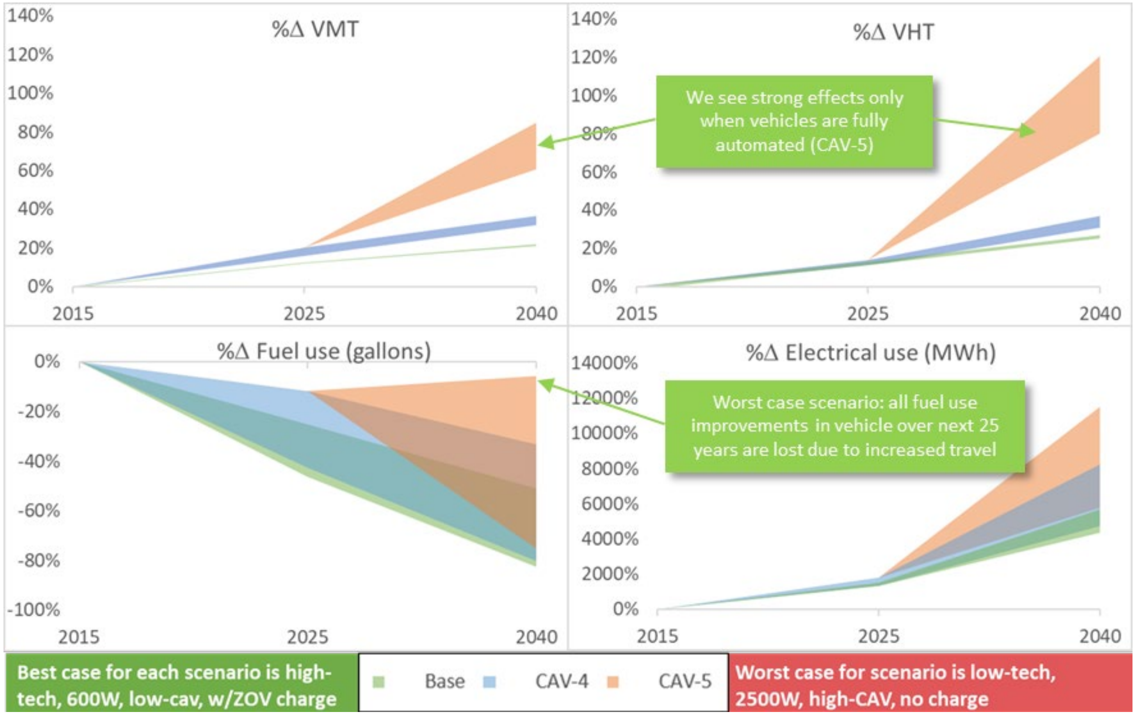


Figure 3-68. Best and worst case performance metrics over time under privately owned, Level 4/5 CAV scenarios.

3.3.2.3 Impacts of Automated SAVs on Energy and VMT

- ZOV trips for personally owned vehicles related to repositioning and other behaviors lead to a significant increase in overall travel, as these vehicles do not achieve the higher efficiencies associated with larger-scale ride-hailing SAV automation.
- High penetration of private AVs (~50%) would lead to a 41% increase in VMT and a 16% reduction in average travel speed, representing substantial congestion growth.

Given the dramatic impacts that privately owned automated vehicles were observed to produce, especially the possibility of increased energy use as well as significantly increased VMT and VHT, one additional possibility considered in this research is the use of shared automated vehicles (SAVs), i.e., automated vehicles operated by TNCs. A case study, highlighted in this document and discussed in much greater detail in the companion SMART Mobility Modeling Workflow Capstone Report (refer to the SMART Mobility Modeling Workflow Capstone Report: Section 4 - Results from POLARIS Workflow Implementation) was performed using the POLARIS model of Chicago that, amongst other scenarios, looked into the impacts of ride-hailing versus privately owned fully automated vehicles. While only the highlights of the results are presented in this document, to provide a contrast between ride-hailing and private fleets of automated vehicles, this work shows some important considerations and impacts related to ride-hailing and privately owned fleets. In fact, privately owned fleets are much less efficient, on an energy use per traveler mile basis, due to zero occupancy miles, than shared fleets of automated vehicles.

Many of the relevant issues leading to this lack of efficiency can be observed below in Figure 3-69, which compares a scenario with high ride-hail use and no private AVs to a scenario with high private AV ownership and low ride-hail usage for the Chicago area. While both scenarios see significant use of shared vehicle assets (i.e., ride-hailing/SAV usage in the shared fleet case and intra-household AV sharing in the privately owned case), there are still significant advantages to be had though usage of ride-hail fleets of automated vehicles: ZOV trips for personally owned vehicles related to repositioning and other behaviors lead to a significant increase in overall travel, as these vehicles do not achieve the higher efficiencies associated with larger-scale ride-hailing SAV automation, which allows for more productive use of the vehicle assets (less empty travel).

Compared with the Chicago metropolitan region baseline case for this study, a significant (52%) penetration of privately owned AVs would lead to a 42% increase in VMT, a 62% increase in VHT, and a 12% decrease in average vehicle travel speed.

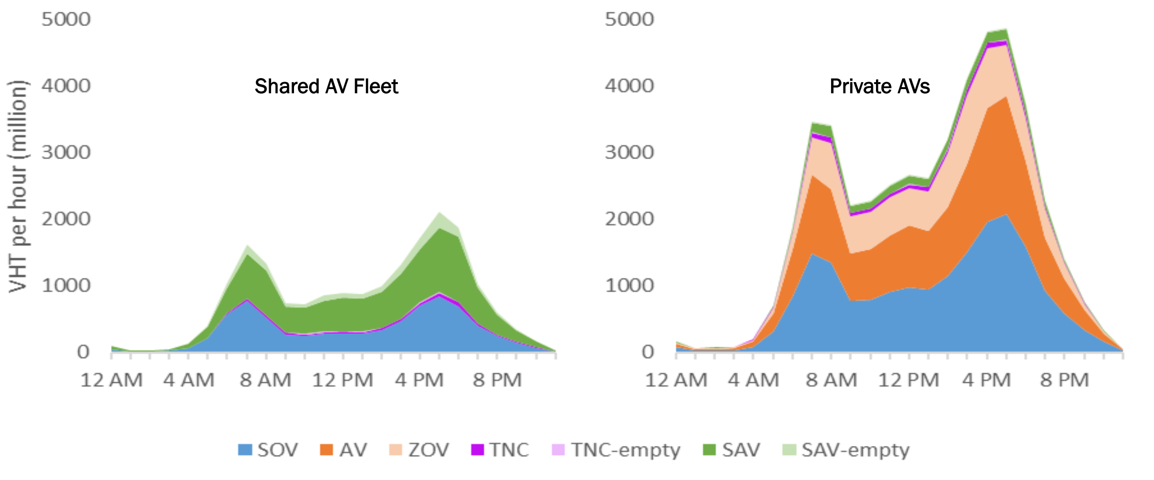


Figure 3-69. Private AV vs. shared AV million travel hours per hour.

3.3.2.4 *Identified Regional Level Mitigation Strategies for Undesirable CAV Impacts*

Incorporating the insights gained from the preceding sections, a range of mitigation strategies has been identified and assessed. More discussion of the implementation and impacts of these mitigation strategies can be found in Section 3.4.3 Promising opportunities to leverage connectivity and automation to offset some of the less desirable regional-level impacts of these technologies include ZOV optimization, improved transit access, leveraging connectivity and automation for improved situational awareness and control, large-scale traveler coordination, managed lanes (possibly including CACC specific lanes), and co-design of vehicle technology to incorporate the new functionalities associated with connectivity and automation.

3.3.2.5 *Summary*

At the regional level, fully automated, privately owned vehicles, if introduced into our near-term transportation system have the potential to substantially impact traffic and energy use through induced demand and zero occupancy vehicles (ZOV), which travel empty due to vehicle repositioning. A preliminary case-study done early in the CAVs Pillar's efforts, showed that VOTT, specifically reductions to VOTT enabled through automation, is a critical parameter driving much of the additional VMT observed in the case study. For example, regional-level modeling based in Bloomington, IL, done within the CAVs Pillar indicates that the presence of fully automated privately owned vehicles would increase trips more than 27% (at low penetration rate/high cost) and 39% (at high penetration rate/low cost). With the combined effect of ZOV travel, this would increase system level VMT by 42% and 63%, respectively.

3.3.3 CAV Transition Dynamics and Identifying Tipping Points

The CAVs Pillar developed conceptual and functional models of CAV adoption to test hypotheses about CAV deployment scenarios.[128] Key takeaways from this work include:

- CAV adoption faces a complex landscape of overlapping stage gates where stakeholders block or accelerate it. Examples include interactions between manufacturer R&D, vehicle miles traveled (VMT) accumulation for insurance underwriting, time for regulatory approval, vehicle costs to consumers, and achieving economies of scale.

- Scenario-screening analyses highlighted influential factors for CAV adoption and energy consumption. Consumer preference, time valuation, and technology costs are particularly strong influencers; others include vehicle powertrain types and fuel economy, proportion of time freed by a particular CAV concept, willingness to pool, road congestion, and amount of deadheading (i.e., extra travel performed by ride-hailing vehicles between passenger-carrying trips).

A conceptual understanding of CAV deployment was developed by representing system relationships from the literature and expert opinion. This was translated into a functional ''CAV scenario generation'' model in systems dynamics using the STELLA simulation tool.[129] The scenario generation model developed in this work is freely available for download on GitHub.[130] This approach improves on human intuition in several ways: It accounts for feedback and shows relationships across the transportation system, enabling development of self-consistent scenarios and helping achieve consensus and shared understanding about what system elements are important and how they interact (such as the interplay between consumers, manufacturers, regulators, insurers, infrastructure investments, etc.). It can be populated with either quantitative or semi-quantitative data with multiple sensitivities regarding uncertainty and the level of detail available in the data. For example, quantitative data would include numbers of vehicles, numbers of miles traveled, and amounts of energy used. Semi-quantitative data would include consumer preference for different vehicle concepts, which is expressed quantitatively in the model but represents a mix of unmeasured and potentially unmeasurable outcomes of hypothetical consumer choices. The model's streamlined data input requirements allow rapid configuration and exploration of new scenarios with sufficient detail to encompass newly emerging empirical data.

The systems dynamics model is organized modularly, where each module represents the behavior and decisions of a sector or stakeholder group. Some modules focus on bookkeeping and accounting of activities, modal choices, vehicle sales, stock, energy, and so forth, while others represent decision making and the choices of the various stakeholders. Influences on the modules are either endogenous feedbacks from other modules or exogenous conditions external to the whole model. Modules within the CAV scenario generation model include the following (additional details on each of these structural elements may be found in the appendix to this CAV Capstone Report):

- Population
- Activities
- Energy
- Travel choice
- Travel time and distance
- Infrastructure
- Vehicles and vehicle requirement
- Manufacturers
- Regulators
- Insurers
- Safety

Multiple assessments and studies were undertaken to identify and develop insights regarding preliminary CAV adoption scenarios. The assessments informally evaluated several CAV adoption hypotheses and identified scenarios of potential interest for deeper analysis using more quantitative, detailed, computationally intensive tools.

The three sensitivity analyses undertaken using the CAVs scenario generation model included a *screening study* broadly exploring stakeholder interactions and CAV adoption futures, an *energy study* assessing factors leading to variability in total energy consumption, and a *comprehensive study* quantifying interactions among stakeholder and energy factors, as detailed in Table 6-4 in the CAVs Capstone Report Appendix. This appendix table contrasts the input parameters varied in these three sensitivity analyses. The three studies use Latin hypercube sampling (LHS) or Sobol experimental designs for 50,000 to 100,000 simulation runs each.

Results of the screening sensitivity analysis provisionally identified conditions for transitions to CAV use and can be refined to focus on conditions of greatest interest. Figure 3-70 shows how each vehicle concept's share of fuel consumption varies with consumer preferences and operating costs. Results range from high-cost, low-preference cases without CAV adoption (lower right corner) to low-cost, high-preference cases with substantial CAV adoption (upper left corner). The figure illustrates a ''tipping point,'' which is defined here as scenarios where a small change in a combination of input parameters results in a disproportionately large change in output metrics: On either side of the diagonal line in the figure, when a small increase in operating cost combines with a small drop in preference for CAV, the market share for CAV falls significantly. With data refinement, calibration, and segmentation, the ranges of parameter space showing various CAV shares could be more quantitatively defined. These results are displayed without detailed quantification, but instead are shown as trends in shares because the data do not warrant excessive precision.

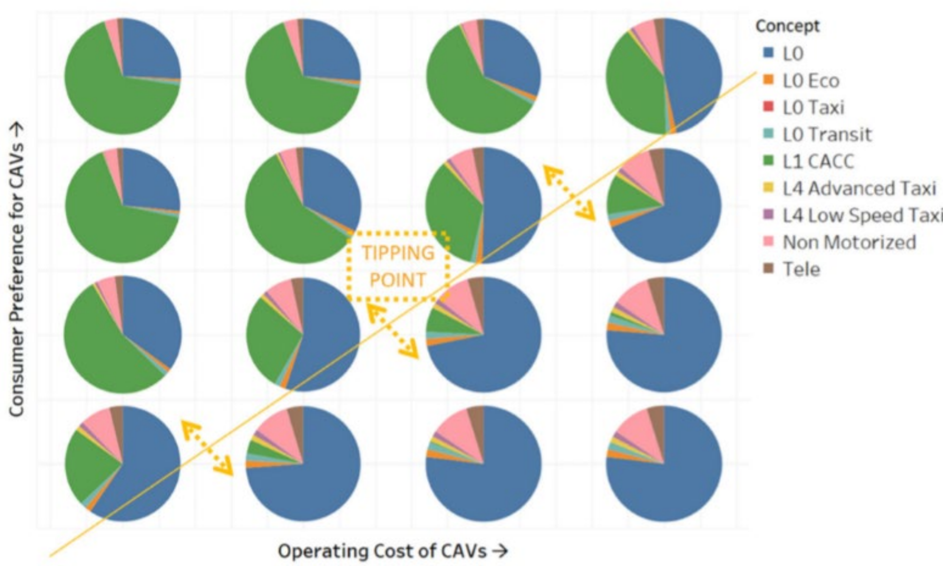


Figure 3-70. Sensitivity analysis (in the screening study) of fuel consumption by concept type nationally in 2040 as a function of the operating cost for L1 and L4 CAV technologies and consumer preference for using CAVs.

CAV adoption faces a complex landscape of overlapping ''stage gates,'' a term which refers to points in the pre-adoption process where upstream stages (R&D, regulation, manufacturing, etc.) must be completed before dependent downstream stages may begin: For example, CAV R&D must reach a requisite maturity before manufacturing can begin. A ''bottleneck'' occurs when an incomplete upstream stage impedes the initiation of downstream stages: For example, insurance underwriting may not become available to consumers until a CAV technology has demonstrated sufficient on-road VMT. Figure 3-71 summarizes the frequency (among the scenarios) of particular stage gates becoming the bottleneck limiting the availability of L4 automated taxis. In many cases, lack of consumer interest or lack of R&D completion blocks availability. In scenarios in which those two stages have been overcome, factors such as infrastructure readiness, vehicle manufacturing, or regulatory approval impose delays but not permanent bottlenecks. Proportions of results in the figure should not be interpreted as probabilities of outcomes because input assumptions do not include probability distributions.

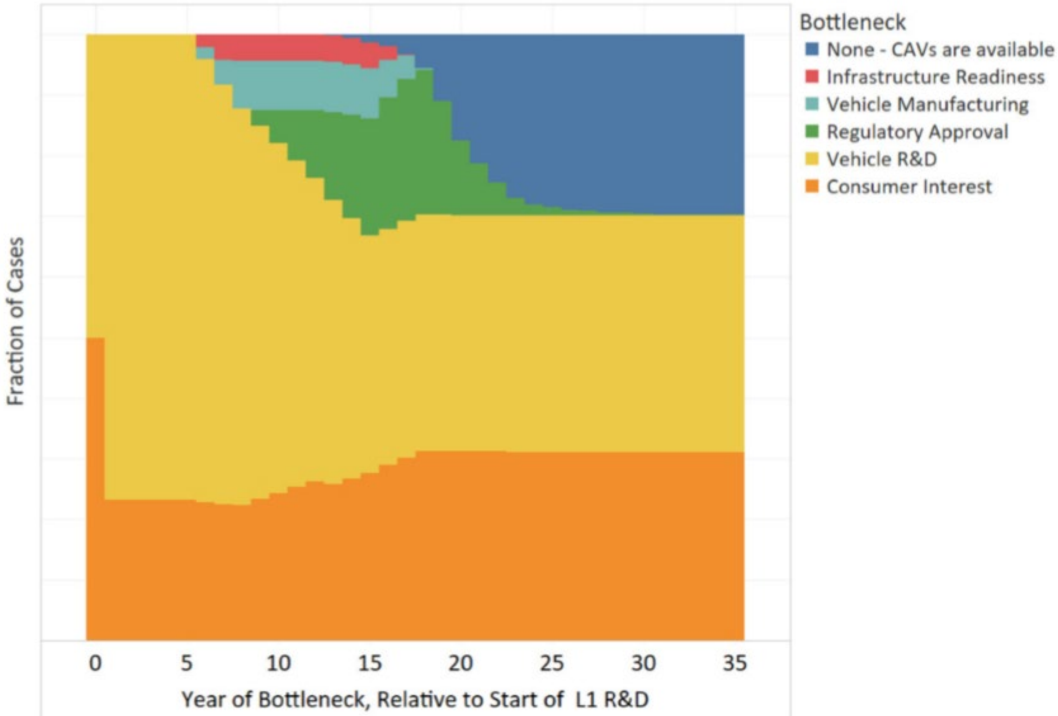


Figure 3-71. Summary (in the screening study) of the frequency of different bottlenecks to CAV adoption among the scenarios.

Figure 3-72 shows a regression tree that indicates that consumer preference and variable costs are the primary influences on the choice of L4 over L1 and L0 concepts. The method used to establish the branching order in this tree ranks factors by the extent to which they distinguish results, such that the most important node appears at the top and the least important ones at the bottom. Each node shows a binary choice that distinguishes two sets of simulations, and the blue wedge shows the share of each set that is in the best 5% for (low) fuel consumption. The fact that there are two paths to low fuel consumption in this figure illustrates that with the diversity of technologies represented, a variety of scenarios may have desirable characteristics. The energy study in the next section shows that significant variation in possible energy outcomes results from the inclusion of deadheading (i.e., extra travel performed by ride-hailing vehicles between passenger-carrying trips).

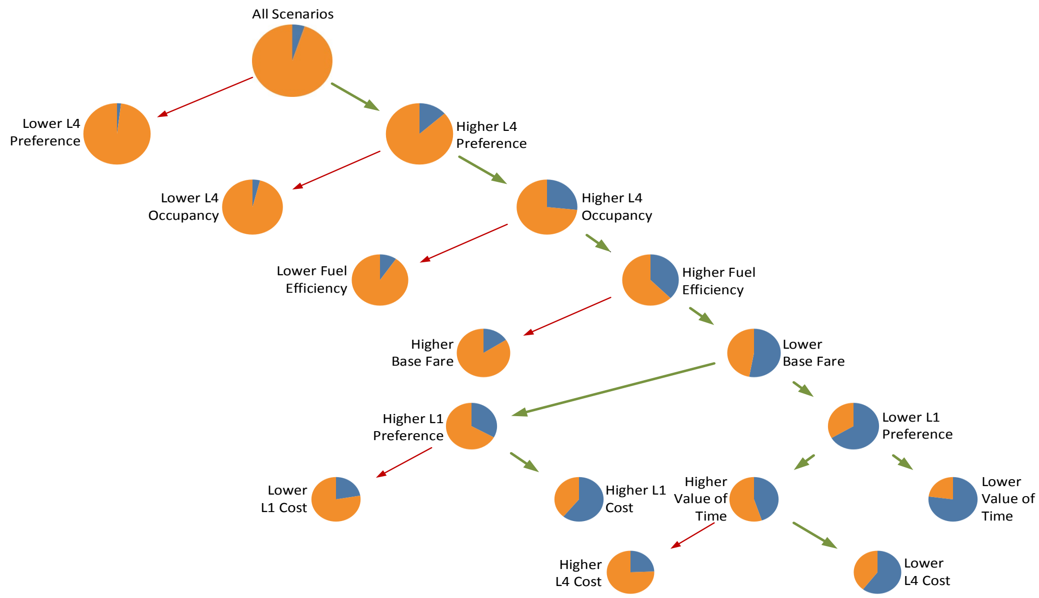


Figure 3-72. Regression tree (for the energy study) showing major influences on energy consumption from tipping points scenario modeling efforts; dark blue in each pie chart indicates the fraction of scenarios that lie in the best 5% of fuel consumption, within simulations selected by the preceding branching criterion.

Scenario-screening analysis results revealed influential factors for CAV adoption and energy consumption. In particular, technological and behavioral assumptions lead to qualitatively different end states for CAVs and energy: As seen in Figure 3-70, small changes in combinations of assumptions can rapidly separate end states of CAV adoption. Multiple evolutionary pathways can converge on similar outcomes for specific metrics, or conversely can diverge to scenarios that yield disparate mobility systems. Figure 3-73 shows more than 2,000 end states with disparate energy and utility profiles: Scenarios in the upper left typically exhibit higher vehicle occupancy, more pooled ride-hailing, higher fuel economy, and fewer deadhead miles, while the scenarios in the lower right generally have lower vehicle occupancy, less pooled ride-hailing, lower fuel economy, and more deadhead miles.

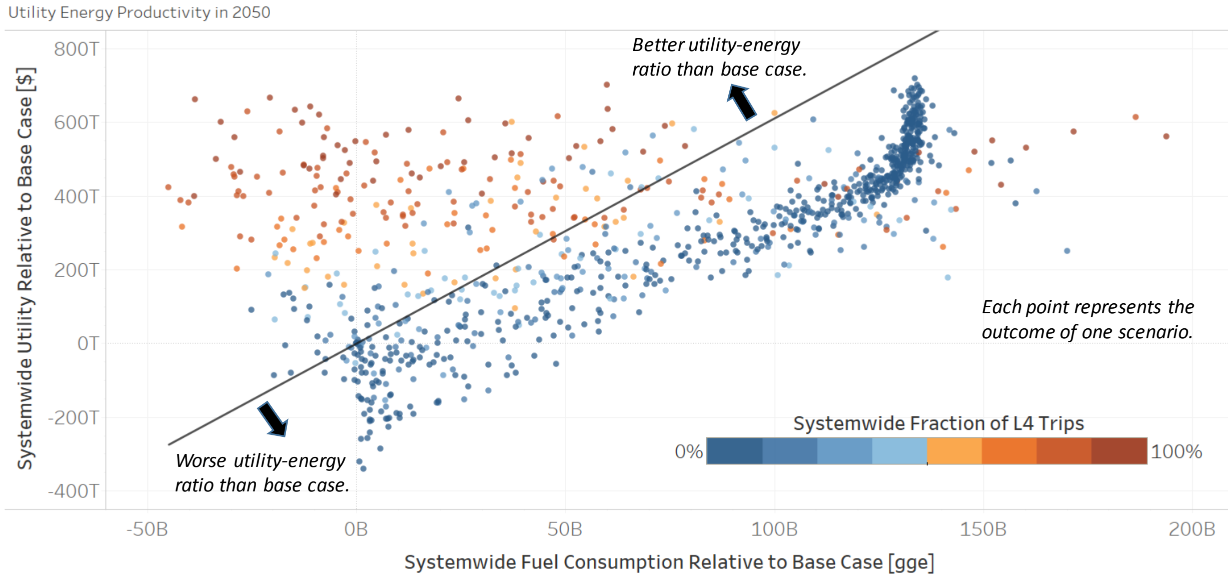


Figure 3-73. Outcomes (for the comprehensive study) with higher "traveler satisfaction" (system-wide utility) tended to require more fuel consumption unless CAVs Level 4 travel concepts predominate. System-wide utilities showed a linear relationship to fuel consumption in low L4 CAV adoption scenarios, but that did not persist at high L4 CAV adoption levels.

Overall, the three sensitivity studies from the CAV scenario generation model yielded the following insights into scenarios for CAVs adoption and energy use:

- CAV adoption faces a complex landscape of overlapping stage gates where stakeholders block or accelerate it. Examples include interactions between manufacturer R&D, VMT accumulation for insurance underwriting, time for regulatory approval, vehicle costs to consumers and achieving economies of scale.
- Scenario-screening analyses highlighted influential factors for CAV adoption and energy consumption. Consumer preference, time valuation and technology costs are particularly strong influencers; others include vehicle powertrain types and fuel economy, proportion of time freed by a particular CAV concept, amount of deadheading, willingness to pool, and road congestion.
- Certain scenarios with high L4 CAV penetration can achieve increased "traveler satisfaction" (system-wide utility) without increasing fuel consumption under the right combination of conditions (e.g., depending on other factors such as time valuation and deadheading). In the absence of high L4 CAV penetration, scenarios with higher system-wide utility tend to require more fuel consumption.
- Massive data gaps and uncertainties regarding future travel behavior, characteristics of CAV technologies, and ownership/business models limit the effectiveness of traditional, fully quantitative choice modeling to assess long-term CAV adoption outcomes; however, use of scenario-based, semi-qualitative modeling can help overcome these limitations.
- Points of leverage fall into three categories: (1) necessary conditions for CAV adoption that impede adoption unless a minimum threshold of support is present, (2) conditions that proportionately accelerate CAV adoption, and (3) conditions not strongly affecting CAV adoption but proportionately affecting energy use. The model can be used to at least qualitatively identify the conditions necessary to reach extremes of technology penetration.
- High adoption of Level 4 may be relatively rare (less than 30% of the scenarios modeled), given the wide range of plausible input assumptions regarding traveler propensities (ownership preference, attitude towards automation, and value of time) and technology characteristics.

- It is feasible to meld the WholeTraveler survey (refer to the SMART Mobility Mobility Decision Science Capstone Report – Section 2.1.1 The WholeTraveler Survey) with the National Household Travel Survey (NHTS) to synthesize traveler cohorts, trip mixes, local deliveries, and mode splits nationally and in the largest metropolitan regions.
- Technological and behavioral assumptions lead to qualitatively different end states for CAVs and energy.
- Small changes in combinations of assumptions may rapidly separate end states of CAV adoption.
- Multiple evolutionary pathways can converge on similar outcomes for specific metrics as well as scenarios that yield disparate mobility systems.

3.3.4 National Level Impacts and Aggregation Techniques for CAV Behaviors and Technologies

CAVs may significantly change mobility and the utility of travel as well as result in large changes in transportation energy use. In SMART Mobility and related research efforts, these potential changes were studied using models and simulations, largely at a regional or local scale. The CAVs Pillar also explored methodologies for synthesizing the regional and local results to a national level.

The following three sections describe approaches that were explored to estimate changes in travel demand (3.3.4.1), aggregate vehicle fuel consumption (3.3.4.2) and CAV technology adoption (3.3.4.3). The goal was to take the results of regional simulations of changes in travel demand, given by VMT and other metrics, and results of vehicle simulations under relevant conditions, and combine these with an estimated mix (stock share) of CAVs and other vehicle technologies to calculate the resulting energy use under scenarios with CAVs. While only partially successful, the results provided fuel consumption aggregation techniques and CAV adoption projections that were used in other SMART Mobility tasks and provided some insights into modeling changes in travel behavior due to CAVs that may be useful to researchers in the field.

3.3.4.1 Transfer Travel Behavior Results from Regional to National Level

- Extrapolating the results of detailed, activity-based, transportation system simulations to other areas or other populations is challenging, especially for travel metrics such as VMT, since VMT depends not only on traveler characteristics, but also on road network characteristics and other land use characteristics at local and regional geographic scales.
- Travel behavior metrics such as trip frequency and time spent traveling can be modeled in a way to enable expanding simulation results to larger populations (given demographic data on the target populations), but it is difficult to relate these metrics to energy use. Traffic flows on road links can be related to energy use, and CAV-induced changes in traffic flows can be modeled at the road or link level, at least in the Chicago metropolitan area. These travel behavior models need further validation before they can be applied to any larger area, such as the entire U.S.

Since detailed, activity-based, transportation system simulations utilize and produce rich sets of data on travel behavior, traveler demographics, land use, and transportation system characteristics, this work explored using such data from the POLARIS simulations of the Chicago metropolitan area to develop models of how travel behavior, especially VMT, changed under a wide range of conditions. It was hoped that such models would be sufficiently robust to be applicable under a wide enough range of conditions to apply nationally. Such models would provide inputs to the aggregation methods described in Section 3.3.4.2 (along with an assumed vehicle mix given by the adoption modeling described in Section 3.3.4.3) to give national-level energy impacts for CAV scenarios.

This work explored ways to expand household-level travel behavior changes resulting from CAVs deployment from POLARIS simulations to the national level. Transferability modeling successfully yielded distributions of the number of trips taken per day and the time spent traveling per day at a national level by bins or clusters of households based on the results of baseline and CACC scenario simulations in POLARIS. However, these travel behavior metrics were not sufficient to estimate VMT, which was the travel behavior metric initially chosen to use in the vehicle fuel consumption aggregation method. Validation testing showed that the resulting VMT models had very poor explanatory power and were unable to model VMT even in the Chicago metropolitan area. Although several model specifications were tried, it was apparent that the explanatory factors used in VMT modeling, which were primarily quantities available from the POLARIS inputs and outputs by household, were not sufficient to model VMT.

As an alternative, another method was developed to estimate changes in traffic flows due to CAVs and was validated for the Chicago metropolitan area. Instead of modeling and transferring VMT for individual scenarios in the Chicago metropolitan area, the change in traffic flows on different links in the road network between a CAVs scenario and the baseline scenario was modeled. If successfully validated for other regions or for the entire U.S., traffic flow projections can then be combined with vehicle-level energy use analysis to give national-level energy use.

Specifically, models were estimated for the changes due to CAVs in the daily flow (vehicles per day) on each network link. The changes in traffic flow modeled were differences between two scenarios: a baseline case (today's traffic flows) and a case with full (100%) penetration by vehicles with CACC. These models take the results of POLARIS simulations for the base case and CACC case as inputs, along with data on the road network, land use, and other variables. Of the several model estimation methods evaluated, models using two machine learning methods yielded satisfactory results: K-nearest neighbors (KNN) and random forest (RF).

Accurately modeling changes in average daily traffic flows (ADTs) requires extensive information about the road network, demographic and land use patterns surrounding each link, and information about the balance of trip production and trip attractions near each link. Over 50 explanatory variables were considered. Variables chosen were of several types: freeway, expressway, ramp, major and minor, collector, and number of lanes. Other link characteristics included link length, connectivity (total number of other connected links divided by the length of the subject link), and distance from the central business district (measured from the link centroid to the CBD centroid). Detailed data on road links and network by type were available from the POLARIS model.

Land use variables included road density, intersection density, population, vehicle ownership, jobs per household, jobs within a 45-minute drive, etc.; these were obtained from the EPA Smart Location database[131], with resolution at the census block group level. Attributes were correspondingly assigned to the links passing through each block group, using a length-weighted average. Additionally, detailed land-use data were obtained for the Chicago metropolitan area from the Chicago Metropolitan Area Agency for Planning (CMAP). CMAP defined eight land use categories: 1) residential, 2) commercial, 3) institutional, 4) industrial, 5) transportation, communication, utilities, and waste land uses, 6) agriculture, 7) open space, and 8) vacant/under construction. Using geographical information system analysis, the area within 150 meters of each link was analyzed and the percentage of area covered by each land use type was assigned to each link. An additional variable, the trip equilibrium index indicating the balance of trip production and trip attractions, was also obtained from the EPA Smart Location database and length-weighted averages were assigned to each link.

Both the K-nearest neighbors (KNN) and random forest (RF) models were developed using a subset of the data (70%) for training and the remaining data (30%) for testing the model. The KNN model achieved an accuracy of 83.5 %, and the RF model achieved an accuracy of 87.1%. In Figure 3-74, predicted ADT values are plotted against test values for both KNN (a) and RF (b) models. In the RF model, factors (explanatory variables) were examined for their explanatory power. Ranking these factors showed that the change in ADT between the CACC and base cases was influenced more by link properties, network properties, and some demographic variables, and less by other demographic variables and land use characteristics.

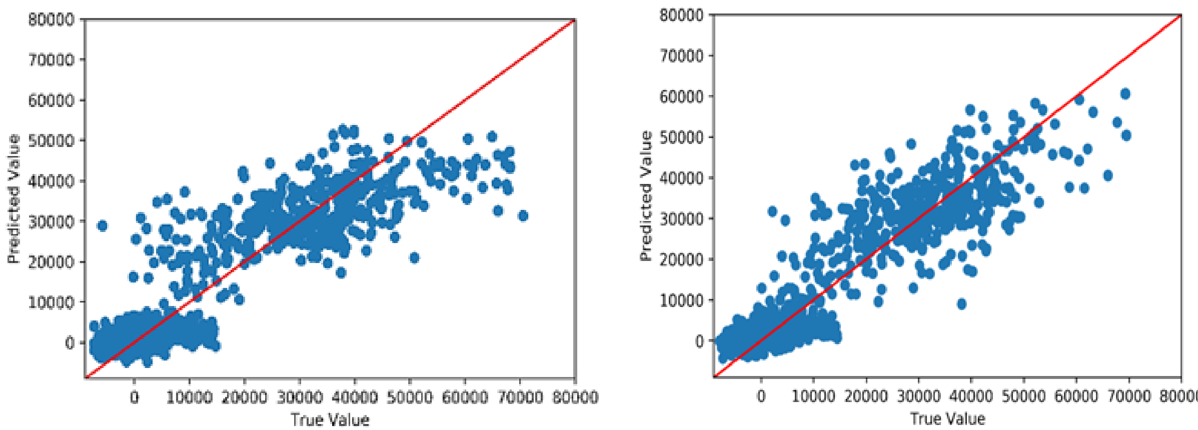


Figure 3-74. Predicted values of average daily traffic (ADT) flows vs true values for the KNN model (a) and the RF model (b).

These models could be used to predict changes in traffic flows on roads throughout the U.S. or at least in other metropolitan areas, provided that data for all the explanatory variables are available, but validation would also require agent-based traffic simulations, such as POLARIS modeling, for additional cities. Due to lack of access to such data, the models were not tested in areas outside the Chicago metropolitan area. Such testing would be the next step towards establishing wider applicability of the models. Once validated, the models for traffic flow changes could be used in a regional or national aggregation or roll-up. A remaining question is whether models can be generalized to predict changes in traffic flows due to deployment of CAV technologies other than CACC, e.g., driverless vehicles, with new users or deadhead travel. It is likely that many of the same explanatory variables would be relevant for modeling changes in traffic flows for these other cases, but it is unknown whether they would be sufficient.

In addition to the potential usefulness of the traffic flow models developed for expanding regional results to larger areas, the models reveal important relationships between the changes in traffic flow and local link, network, demographic, transportation, and land use characteristics. Details of the links, the network, and some demographic variables have a significant influence on traffic flows on network links. Further examination of how these factors influence CAVs-induced changes in traffic flows under different conditions may be helpful in understanding system-level interactions between the factors how CAVs can change travel patterns and energy use.

3.3.4.2 Vehicle-Level to National-Level Fuel Consumption Aggregation

- A functional framework was developed and demonstrated for rolling up national-level energy consumption estimates under different scenarios.
- This framework has been adapted and similarly used to roll up energy consumption estimates at the level of individual road links and/or at the level of an entire city/metropolitan area.

The previous sub-section described efforts to transfer impacts on parameters such as VMT in prospective regional-level scenario analyses to the national level. This sub-section describes the methodology developed to estimate national-level energy consumption based on VMT and other analysis inputs. This methodology involves first selecting the set of vehicles to be considered in the analyses, then estimating the fuel efficiency of each considered vehicle over a matrix of driving conditions that may be encountered. These matrices for each considered vehicle can then be multiplied by the corresponding vehicle miles travelled in each driving condition by each vehicle type. Note that this matrix multiplication can occur at the level of an individual road link, at the level of a city road network, and/or all the way up to the national level. Each driving condition in the matrix multiplication is defined by a set of parameter dimensions, and the structure of the framework affords some level of flexibility in selecting the dimensions that work best for a given application. Typical dimensions include factors such as road type/category, number of lanes, traffic speed/congestion level and road grade. Dimension selection for a specific application is influenced by the availability of disaggregated VMT data into consistent dimensional bins (to enable the matrix multiplication for that application).

Within the selected dimensional framework, a given vehicle's fuel consumption rate under each combination of driving conditions may be determined directly from on-road test data (as was done in the collaboration with Volvo Cars Corporation described in Section 3.1.4). These relationships may alternately be estimated by simulating a model of the vehicle over a large set of real-world driving profiles that encompass the desired spectrum of driving dimensions, such as running FASTSim vehicle models over driving profiles from the TSDC. As described in Section 3.1.6, RouteE models calibrated following this process can be used for green routing as well as for energy aggregation applications.

To establish a tractable mechanism for rolling up fuel consumption calculations to the national level, a large database of typical hourly traffic speeds/road congestion levels across the U.S. (from the mapping company TomTom Technology) was conflated with daily VMT for road links across the U.S. (from the FHWA Highway Performance Monitoring System (HPMS) database). Details of this process and the resulting national-level VMT database disaggregated by road type and traffic speed/congestion level are available in a Transportation Research Record (TRR) journal publication.[132]

A broader framework enabling exploration of the national-level energy impact of hypothetical CAV introductions was subsequently built around this core capability to roll up vehicle fuel consumption under specific driving conditions with the VMT occurring in each condition. Feature additions included integrating a model to track evolution of the national vehicle stock through vehicle retirements and introductions. Another feature modeled new vehicle efficiency improvements over time, along with driving-condition-specific efficiency implications from given CAV technologies as they enter the market. Figure 3-75 shows a flowchart of this full modeling framework, and Figure 3-76 shows that prototype application of this bottom-up calculation approach for a non-CAVs scenario compares favorably with the Annual Energy Outlook (AEO) reference case produced using a different methodology.[133]

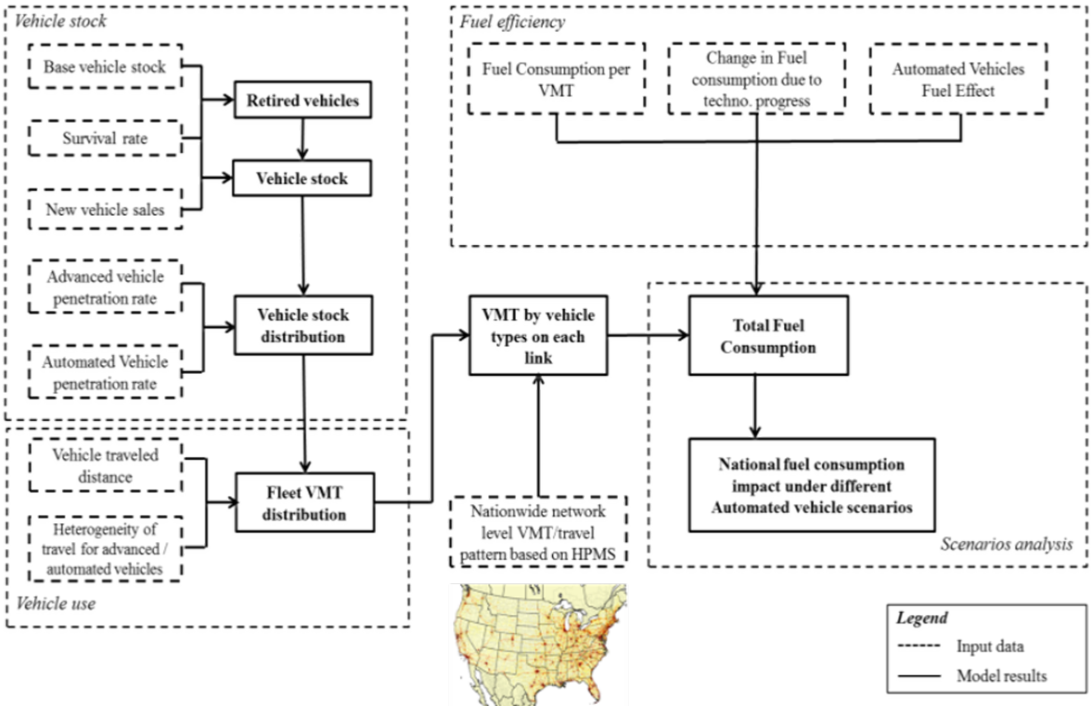


Figure 3-75. Flowchart of the prototype modeling framework for generating bottom-up national-level energy estimates under different scenarios.

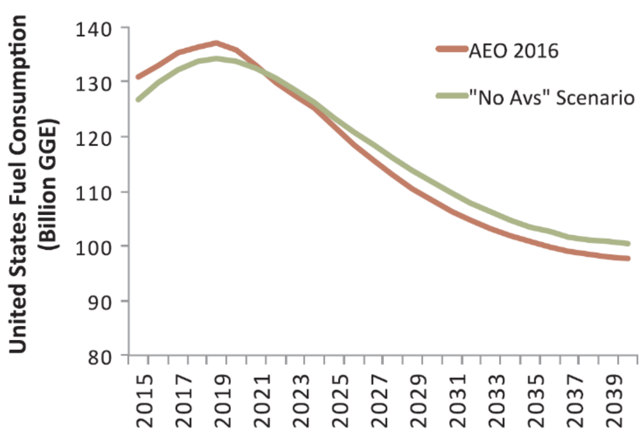


Figure 3-76. National-level fuel consumption estimates for a preliminary non-CAVs ("No Avs") scenario using the prototype bottom-up calculation framework, compared with the 2016 AEO reference case produced with a different methodology.

While this bottom-up energy estimation approach showed promise for analyzing different national-level CAV scenario impacts, challenges associated with the VMT transferability work covered in the previous section did not allow for its timely application to scaling up detailed regional-level scenario simulations to the national level. Nevertheless, the approach found immediate application for estimating vehicle and link-level energy consumption in the San Francisco Bay area implementation of the SMART Mobility Workflow centered on the BEAM model (and subsequent city/metropolitan-area energy consumption aggregation under various evaluated scenarios). Many more details on this can be found in the SMART Mobility Modeling Workflow Capstone Report.

3.3.4.3 CAVs Technology Adoption

- Highly automated vehicles are expected to become a large portion of projected future personal and/or shared-mobility fleet vehicle sales given that they offer significant consumer benefits, including reduced travel time costs (due to reduced personal value of travel time) through more productive use of travel time as enabled by a reliable automation system.
- In addition to the reduced travel time costs, a high level of automation is valuable for limited-range BEVs since the gain in energy efficiency (due to more efficient vehicle driving dynamics and routing) results in extended range and reduced range anxiety.
- The introduction order of personally owned highly automated vehicles versus ride-hailing based highly automated vehicles is important. If first adopted as personal vehicles, highly automated vehicles may increase personal vehicle ownership. In contrast, if highly automated vehicles are first adopted at a significant scale as ride-hailing vehicles, a decrease in personal vehicle ownership is expected.
- Additional travel demand induced by automation could mean an increase in personal automated vehicles or a more moderate increase in fleet-own shared automated vehicles that are used more intensively at a higher occupancy. This has implications on vehicle scrappage, design and cost, and so is relevant for the automotive industry.

The adoption of CAVs and their energy implications is complicated by interactions with shared mobility and electrification technologies. Vehicle automation may lead to additional travel demand it terms of passenger miles traveled (PMT), but the impact on overall vehicle miles traveled (VMT) depends on how closely and efficiently automation is coupled with shared mobility. Moreover, without electrification or better fuel efficiency, the increase in VMT due to this additional travel demand may worsen the overall energy and environmental impacts of personal vehicles. To model and analyze the adoption and synergy of vehicle automation, electrification and sharing technologies, a consumer choice model called MA3T-MC was developed by expanding the existing MA3T model, which focused on consumer preference for different fuel types, to cover consumer preference for connected and automated vehicle technologies and services.[134]

Key results from MA3T-MC related to CAVs outcomes include:

- Significant consumer benefits due to reduced travel time cost (mainly due to reduced cost of unit travel time or more productive use of travel time enabled by the automation system, and to a lesser extent due to reduced travel time from optimal routing), reduced driving stress, and reduced insurance premiums (an approximate but probably low estimate of safety value)
- Extended range and thus reduced range anxiety for short to moderate range BEVs due to more efficient automated driving
- A possibly significant surge in personal vehicle sales due to the significant consumer benefits of automated vehicles shortly after their assumed introduction to the market in 2030
- A possible decrease of personal vehicle sales when automated ride-hailing becomes more affordable and reliable

MA3T-MC estimates consumer preference based on bottom-up calculation of generalized costs. In general, the lower the total generalized cost of a choice, the more attractive it is to consumers. Figure 3-77 shows the components of consumer generalized costs for human-driven vehicles (HV) versus highly automated vehicles (AV) of different powertrains: spark-ignition (SI) vehicles, battery electric vehicles (BEV), and plug-in hybrid electric vehicles (PHEV) in 2035 and 2050. The comparison of generalized cost components between 2035 and 2050 illustrates the underlying dynamics that lead to sales impacts. As shown, travel time cost represents the largest cost component. The reduction in travel time cost becomes deeper over time due to improvements in automation reliability and increased utilization of in-vehicle time for productive activities. The reduction in driving stress cost is also significant and becomes deeper over time. Insurance premium reduction is not as large as reduction in travel time cost or driving stress cost but is clearly greater than the reduction in energy cost. The decrease in range anxiety cost in short-range BEVs (between HV-BEV100 and AV-BEV100) due to efficient automated driving is also noticeable. This is based on the assumption of more efficient vehicle driving dynamics and routing as well as a minimal energy burden from onboard sensing and computing by 2050.[135] Overall, travel time cost reduction is the most important consumer benefit, followed by reduction in driving stress and insurance premium.

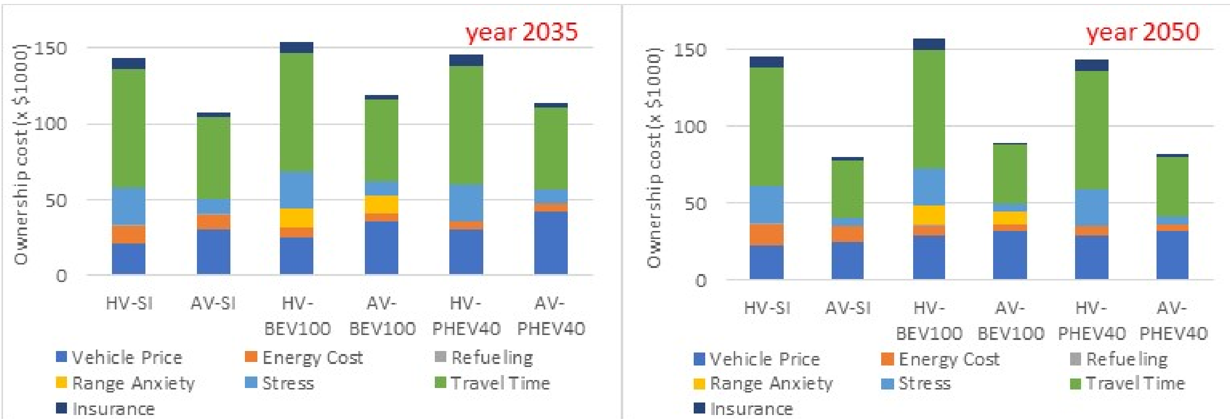


Figure 3-77. Components of consumer generalized cost modeled in MA3T-MC in years 2035 (left) and 2050 (right) for human-driven vehicles (HV) and automated vehicles (AV).

Building on the projected generalized costs shown above, total vehicle sales, shown in Figure 3-78, for a scenario in which personal AVs and ride-hailing fleet AVs enter the market simultaneously (subfigures a1 and b1), show a rapid increase in sales of personally owned automated vehicles shortly after the introduction of CAVs in 2030, due to the significant consumer benefits associated with automated vehicles as illustrated on Figure 3-77. Following this initial increase in overall vehicle sales, the model projects a decrease in personal and overall vehicle sales after 2040, when automated ride-hailing becomes more affordable and begins to replace personal travel and vehicle purchases. Growth of PMT is assumed to accelerate after AV introduction, reaching 30% more than without AVs (Figure 3-78 b1) by 2050. Served by a combination of personal AVs and fleet-owned shared-mobility AVs, AV ride-hailing becomes more efficient and affordable and captures about 65% of PMT by 2050. The increasingly popular AV ride-hailing services make personal vehicle ownership less necessary and attractive, and after 2040 begin to suppress personal vehicle purchases.

The impact of CAVs on vehicle sales can be uncertain for many reasons, one of which is related to the timing and extent of AV introduction: whether personally owned vehicles or fleet-owned shared-mobility vehicles. In contrast to the AV2030 scenario, Figure 3-78 (a2) shows overall vehicle sales for the SAV10yr Earlier scenario, in which efficient and affordable TNC AVs enter the market in 2030 while the personal AV market entry is pushed to 2040 (possibly due to factors such as technology readiness, vehicle-level costs, company strategies or simply regulation). In this scenario, a significant shift in household travel towards ride-hail AVs can be observed in the PMT subgraph (b2) as well as a minimal increase in overall vehicle sales (a2) after 2040 due to the higher expected utilization of ride-hail AVs (assumed to continuously run over 10 hours per day) versus personally owned vehicles. The personal vehicle sales drop significantly during the period 2030-2040, when AVs are only available as fleet-own shared-mobility vehicles, as efficient, affordable AV ride-hailing offers much greater value on travel time cost reduction and driving stress reduction than human-driven personal vehicles. Total vehicle sales are compensated by the sales of fleet ride-hailing AVs, but still drop somewhat due to the higher utilization and higher occupancy of these vehicles joining to serve the same amount of PMT. For the SAV10yr Earlier scenario, in which personally owned AVs become available in 2040, there is an increase in total vehicle sales due to personal AVs appealing to a certain segment of the population, but total vehicles sales are still well under the 2040 and beyond levels from the AV2030 scenario. This modeling result suggests that in the future, coupling rapid large-scale adoption of ride-hailing and highly automated vehicle capabilities may result in a significant shift of primary personal or household travel away from other modes towards ride-hail AVs. Moreover, these trends carry into the future, as evidenced by the 2050 mix of ride-hail PMT (subfigure b1 versus b2), suggesting that once the shift to ride-hailing occurs, it does not necessarily reset if personal AVs are later introduced. Between the two scenarios, although the total PMT trajectory is similar, the mix and total of vehicle sales are very different, mainly resulting from the relative timing of AV introduction to the personal and fleet TNC markets. This suggests that additional travel demand induced by automation could mean proportionally more personal automated vehicles or moderately more fleet-owned shared automated vehicles that likely are used more intensively at a higher occupancy. This increased usage intensity has implications on vehicle scrappage, design and cost and thus could be relevant for consideration by the automotive industry.

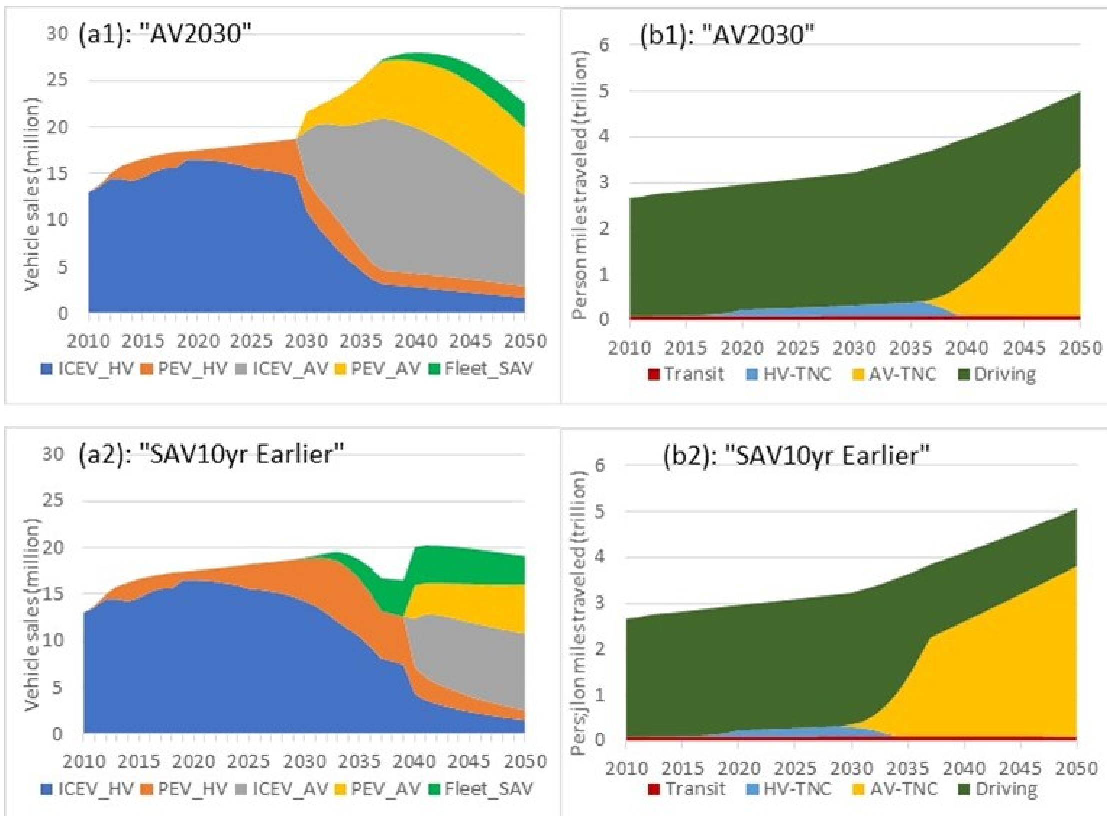


Figure 3-78. (a1) (a2) Projected vehicle sales by powertrain and automation (ICEV: conventional internal combustion engine and non-plug-in hybrid electric vehicles; PEV: plug-in hybrid electric vehicles and battery electric vehicles; HV: human driven vehicles; AV: highly-automated vehicles), and (b1) (b2) projected passenger-miles traveled by the primary mode of household (HH) travel; TNC: transportation network companies, i.e., ride-hailing; Driving: driving personal vehicles. The top two graphs (a1) and (b1) represent the AV2030 scenario in which personal AV and ride-hailing AV both enter the market in 2030 and improve over time. The SAV10yr Earlier scenario shown in the bottom two graphs (a2) (b2) assume that fleet-owned ride-hailing AVs enter the market in 2030 with technology maturity while personal AV market entry is pushed to 2040.

The results from MA3T-MC are not intended to be a perfect prediction of future CAV adoption. However, the results provide some important insights into the market dynamics of CAV adoption. If perceived by consumers as reliable and safe, as well as priced reasonably, highly automated vehicles could quickly dominate the market as either personally owned vehicles or ride-hailing vehicles. The assumption of perceived reliability and safety is critical to market adoption and could be examined by more research. Another key takeaway is that the impact of vehicle automation on personal vehicle ownership depends on whether highly automated vehicles are first used as personal vehicles or ride-hailing vehicles. This also has implications for the automotive industry's vehicle design and supply strategy. The MA3T-MC results also suggest the importance of more research to quantify the value of CAVs on reducing driving stress and increasing productivity of travel time, thereby reducing an individual's travel time cost.

3.4 Harnessing Connectivity and Automation for Improved Energy Outcomes and Coordination

In contrast to the previous section, which focused on impacts of CAV technologies operating within the current and near-term transportation infrastructure, this section directly focuses on how to leverage the new capabilities afforded to CAVs through improved awareness, controllability, coordination, and connectivity to reduce fuel consumption and increase mobility. Specifically, this section summarizes work towards the pillar's third research question: **"What is the best way to harness CAVs for reduced energy use and improved mobility in transportation?"** In this section, the possible traffic flow and efficiency benefits due to the additional information available to and controllability afforded by CAVs are quantified in multiple scenarios for an individual vehicle, corridor, region, or city, including sensitivities due to different penetration levels and varying degrees of automation. The section begins with a study and development effort to demonstrate how connectivity and automation can enable energy savings through "vehicle-centric" predictive control and co-optimization of both powertrain operation and speed. The resulting energy-saving techniques can then be tailored to various vehicle classes, use cases and vehicle technology scenarios (e.g., hybrids, EVs). Additional research in this section investigates corridor-level approaches, including advanced traffic management strategies and a framework for optimal vehicle coordination across a range of traffic scenarios. Finally, this section discusses regional-level strategies to mitigate some of the less desirable aspects of certain anticipated automated vehicle use cases. Broadly speaking, this section seeks to investigate how driver feedback systems, improved controls, situational awareness, optimized coordination, and other strategies can be combined to better control connected, non-automated vehicles as well as CAVs for less energy intensive and higher roadway throughput outcomes.

Key controls insights and results include:

- A single vehicle with intelligent powertrain and speed control algorithms developed by the SMART mobility consortium was shown to reduce energy/fuel consumption up to 15% alone, and up to 22% when integrated with Vehicle-to-Infrastructure communication of traffic signal information in real-world driving conditions by adapting to the road topography, surrounding vehicles, and the sequencing of traffic lights.
- Highlighted findings from the large-scale study to evaluate the energy impacts of various eco-driving algorithms in a broad range of driving conditions, powertrains, and technology time frames include:
    - Eco-driving saves more in city driving (up to 22%) than in highway driving (up to 6%).
    - Speed+powertrain eco-driving typically saves more than the speed-only eco-driving — between 4 and 9 percentage points more — by considering the best operating points in the powertrain.
    - V2I-enabled traffic light eco-approach typically increases eco-driving energy savings. In fact, Speed-only eco-driving with V2I saves more than the speed+powertrain without V2I for EV and conventional powertrains in urban and suburban conditions.
- While energy savings from eco-driving are greater for the lead vehicle than for the following vehicle, non-equipped vehicles can also experience energy savings of up to 8% when following a vehicle equipped with eco-driving.
- U.S. Department of Energy Vehicle Technologies Office advanced technology targets for engine efficiency improvements at low loads will lead to higher energy savings from eco-driving for conventional vehicles in future technology scenarios — up to 6 extra percentage points in the 2025 target — compared to savings from business-as-usual technology improvements.
- The intelligent powertrain and speed control algorithms developed and integrated within this work utilized RoadRunner to ensure real-world eco-driving capable systems and incorporate uncertainties, perturbations, and dynamics.

- Corridor-level microsimulations showed that ACC vehicles with V2I capability could follow roadside variable speed limit/advisories (VSL/VSA) to maintain a set speed, which could improve traffic throughput compared to traffic with 0% ACC and without V2I. For V2I capable ACC vehicle penetrations of 10%–30%, results in the simulated corridor showed that total travel time (TTT) could be reduced by ~6-7%, speed variation could be reduced by 8%, and total delay could be reduced by 9~11%.
- For signalized urban intersections, simulation results with and without CACC operating through a standard four-way signalized intersection, show a 67% capacity increase for the major approach and a 49% capacity increase for the minor approach when the CACC market penetration increases from 0% to 100%. While this throughput increase is generally a positive development it is not necessarily optimal. In higher CACC market penetration cases the CACC string may prevent a vehicle needing to switch lanes or turn to find a gap upstream from the intersection and thus the vehicle is forced to make aggressive last-minute lane changes near the intersection leading to an interruption in queue discharge flow.
- At a signalized intersection, if active coordinated traffic signal control is used to integrate the CACC vehicle operation with the signal control, capacity will increase with the market penetration levels of CACC vehicles. With 100% market penetration, this capacity increase is about 75%; fuel consumption would increase by 70%.
- For vehicles operating in a controlled merging zone and amid partial penetration of CAVs and heterogeneous fleet (i.e., different vehicle classes from light-duty to heavy duty), the consortium-developed optimal coordination framework for CAV merging can provide 3% to 30% fuel savings for a highlighted freeway merging scenario under moderate to heavy traffic.
- For vehicles crossing a roundabout with a full penetration of CAVs, the optimal coordination framework can save up to ~27% fuel and between 3% to 49% of travel time depending on the traffic conditions.
- For a simplified highway corridor, at full penetration of CAVs, the developed optimal coordination mitigates traffic jam propagation leading to travel time savings of up to 40% and improvements in fuel economy of up to 55% over the non-coordinated scenario. For a longer, real-world corridor, at lower CAV penetration levels, the developed coordination framework still achieves a significant benefit to overall corridor fuel consumption reduction. For example, at 20% CAV penetration, a benefit of 4% is achieved.
- At the regional level, a decrease in overall fuel usage of 1.1% could be accomplished in the Bloomington, IL study region by subsidizing ride-hailing access to transit stops, resulting in an 11% increase in transit ridership. Similarly, ZOV pricing of $0.33 per mile would reduce overall ZOV miles by 25%, helping to mitigate the potential impacts of widespread private AV adoption
- A regional-level coordinated platooning study found that high wait times associated with joining a platoon, which can increase the total time that vehicles spend in platoons, may only lead to moderate energy savings due to issues with platoon formation.

3.4.1 Eco-Driving: Energy-Focused CAV Control Development

- A single vehicle with intelligent powertrain and speed control algorithms developed by the SMART mobility consortium was shown to reduce energy/fuel consumption up to 15% alone, and up to 22% when integrated with Vehicle-to-Infrastructure communication of traffic signal information in real-world driving conditions by adapting to the road topography, surrounding vehicles, and the sequencing of traffic lights.
- Large-scale simulation studies have shown these benefits to vary significantly depending on scenario and powertrain technology, with BEVs showing up to 7% reduced consumption.

In addition to safety, comfort and mobility promises, driving automation can also be leveraged for increased energy efficiency. Most "self-driving" driving research and development has been focused on developing sensors, machine vision, and controls that enable safe operations in a broad range of conditions. Energy-focused CAV controls use the speed control offered by driving automation to make the vehicle drive more energy efficiently. Partially automated driving features already offered on production vehicles, such as adaptive cruise control, can control the longitudinal speed while avoiding collisions with preceding vehicles and offer convenience to the driver. These controls use the information about the surrounding environment such as road topography (from digital maps), state of surrounding vehicles (from sensors), current and future states of traffic lights, traffic and vehicles beyond sensing range (from V2X communications). Energy-focused optimization can then compute how to best drive the vehicle for minimum energy consumption without negatively compromising safety, comfort, and travel time.

RoadRunner, introduced in Section 3.2.1, serves as a simulation platform for the development of energy-focused CAV acceleration and powertrain controls and enables the simulation of a wide range of CAV situations and scenarios. Several models were developed and validated from test data (3.4.1.1) to model in the RoadRunner simulation platform, including both existing CAV technologies and human driving. "Eco-driving" CAV control algorithms, which optimize the driving and optionally the operations of vehicles for energy efficiency, were developed for vehicles with advanced powertrains (3.4.1.2) with a major focus on real-time implementation capability (3.4.1.3). A large-scale case study (3.4.1.4) was then performed in RoadRunner to quantify the energy-saving potential of these algorithms for a broad range of scenarios, using the validated human driver as a baseline.

3.4.1.1 RoadRunner Model Validation

- A model of platooning trucks was developed and validated in RoadRunner from track-testing data; simulated energy and driving dynamics match test data within 7%.
- The adaptive cruise control featured in a production Toyota Prius was replicated in RoadRunner, following data collection on a chassis dynamometer.
- A human driver model was developed to serve as baseline for CAV studies and matches the sub-second driving dynamics recorded in the real-world with over 95% accuracy.

The development of new controls is done in simulation before being demonstrated and refined in the real world. SMART Consortium researchers developed a new platform, RoadRunner (3.2.1) specifically to enable research in eco-driving controls for CAVs. RoadRunner includes a collection of CAV and powertrain models and controls, the building of which is presented here. In order to demonstrate the soundness of the approach, several CAV models in RoadRunner were validated using real-world data, including truck platooning and light-duty adaptive cruise control. A human driver model was also developed (3.4.1.1.3), and can be used as a baseline for the evaluation of CAV control energy benefits.

3.4.1.1.1 Truck Platooning Model Validation in RoadRunner

Automated trucks can be more responsive to speed changes than manually driven trucks. As a result, automated trucks can safely travel at a shorter following distance, which increases roadway capacity and improves mobility. In addition, shorter following distances can reduce aerodynamic drag and consequently reduce fuel consumption. Following the test of three platooning trucks on a test track (See Section 3.1.3), a corresponding scenario was developed in RoadRunner and the driving dynamics, powertrain operations and energy consumption were validated.[136]

The modeling and validation process is shown in Figure 3-79. The first step is to develop a model of the powertrain in Autonomie and validate it for the lead truck — the driving dynamics of the lead vehicle are simply modeled by using the recorded speed as the "drive cycle." This process includes validating the gear shifting patterns as well as the instantaneous fuel flow rate. The lead vehicle fuel consumption was validated to within 1% of the test data. The second step is to focus on replicating the dynamics of the following vehicles. A cooperative adaptive cruise control algorithm was developed and implemented for the two following vehicles and calibrated to match the behavior of the trucks in the real-world experiments. Finally, a scenario replicating the on-track test was simulated in RoadRunner. Figure 3-79 compares the driving and fuel consumption dynamics of the second vehicle in the platoon in simulation and in test. Table 3-9 summarizes the results for all three vehicles. Overall, the gap and fuel consumption closely matched.

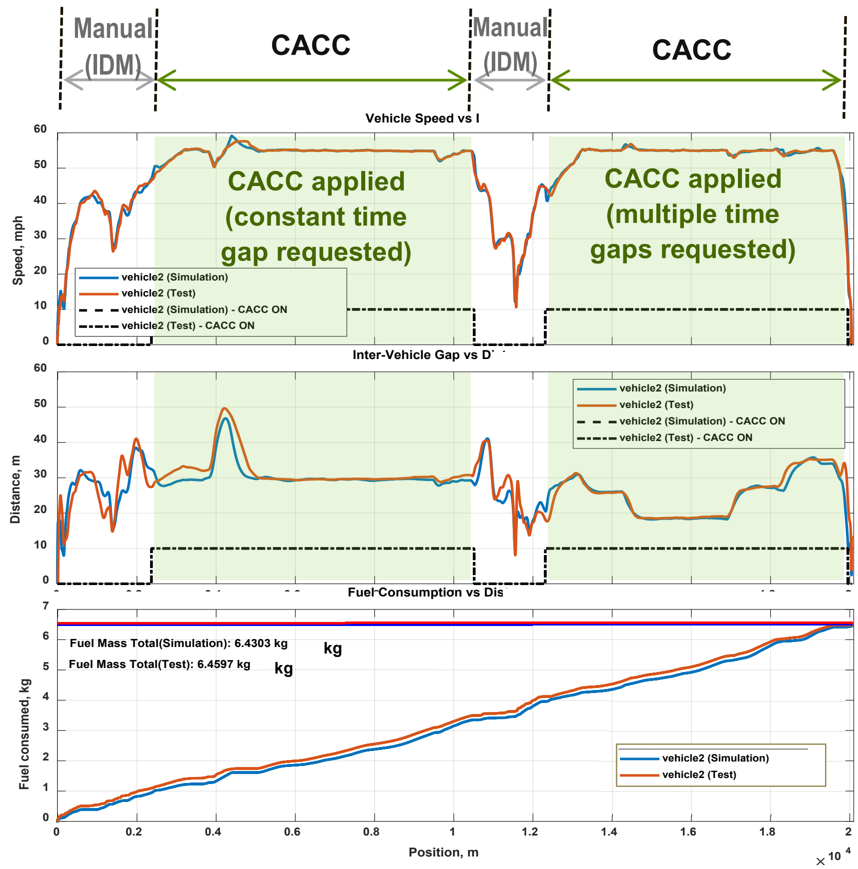


Figure 3-79. Speed, inter-vehicle gap and fuel consumption for middle vehicle in platoon, in test and in simulation

Table 3-9. RoadRunner Truck Platoon Validation Summary.

Cycle (0–20,050 m)		Travel time, sec	Average gap, m	Fuel consumption, L/100 km
Veh1 (Lead)	Test	997.3	-	38.78
	Simulation	997.5	-	38.56 (-0.6%)
Veh2 (Middle)	Test	979.9	25.9	38.57
	Simulation	972.7	25.1 (-3.1%)	38.39 (-0.5%)
Veh3 (Trailing)	Test	971.0	30.3	41.05
	Simulation	969.5	29.3 (-3.3%)	39.40 (-4.0%)
CACC #1 (constant time gap)		Travel time, sec	Average gap, m	Fuel consumption, L/100 km
Veh2 (Middle)	Test	333.7	30.4	35.13
	Simulation	333.4	31.7 (4.3%)	35.31 (0.5%)
Veh3 (Trailing)	Test	350.8	31.0	36.30
	Simulation	350.0	30.4 (-1.9%)	36.19 (-0.3%)
CACC #2 (variable time gap)		Travel time, sec	Average gap, m	Fuel consumption, L/100 km
Veh2 (Middle)	Test	319.9	25.6	36.88
	Simulation	318.3	25.2 (-1.6%)	38.56 (4.6%)
Veh3 (Trailing)	Test	305.4	21.4	37.36
	Simulation	303.4	22.5 (5.1%)	40.09 (7.3%)

3.4.1.1.2 Passenger Car Adaptive Cruise Control Model Validation in RoadRunner

Many new vehicles already feature partial driving automation, for example longitudinal speed control for highway driving. With adaptive cruise control (ACC), the vehicle drives at a speed set by the driver if no preceding vehicle is detected (using a radar or stereoscopic cameras), and otherwise modulates its speed to maintain a safe distance from the preceding vehicles. The ACC feature of the 2016 Toyota Prius Prime was tested on a chassis dynamometer, and a model of the vehicle and the ACC was then developed within RoadRunner and validated. In order to test the ACC feature with no actual moving vehicles to detect, a method of overwriting the gap measurement from the sensor was designed and implemented. As a result, it is possible to test a situation where the ACC controller commands the actual vehicle on the dynamometer to follow a virtual lead vehicle, itself following a set drive cycle. This setup allows the CAV Pillar researchers to evaluate the automated driving controller in a laboratory environment. The data from the dynamometer test, and the inter-vehicle gap data especially, was then used to validate an ACC model in RoadRunner, in which the powertrain model had been validated in Autonomie.[137] As shown in Figure 3-80, the inter-vehicle gap is fairly well matched to the data from the dynamometer.

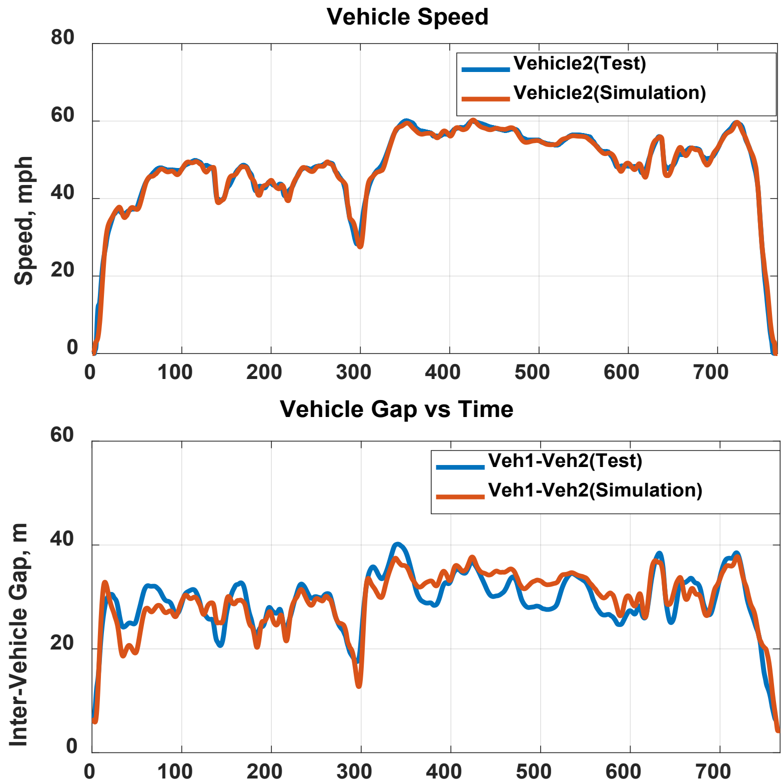


Figure 3-80. Comparison of the ACC model in RoadRunner with test data from the chassis dynamometer. Vehicle 1 is driven by a human. Vehicle 2 is outfitted with the ACC system.

3.4.1.1.3 Human-Driver Model Validation in RoadRunner

Modeling the human driver is critical for the development and evaluation of powertrain/driving controls relying on automation and connectivity. With a high-fidelity human driver model, it is possible to model in simulation an energy-optimized vehicle surrounded by modeled vehicles realistically replicating human driving behavior. A good human driver model is also necessary to serve as a baseline when evaluating the potential benefits of new control algorithms. As a result, combining data-driven and analytical approaches, a high-fidelity dynamic human driver model was developed and integrated into the RoadRunner framework.[138] The design of the model was driven by three key considerations: 1) *simplicity*, for computational efficiency, 2) *accuracy*, describing the detailed dynamics of driving, and 3) *variety* resulting from internal (e.g., driving style) and external factors (e.g., traffic signals).

To this end, the human driver model consists of two parts: a *perception and decision* (P&D) model and an *action* model, as shown in Figure 3-81. The P&D model aims to capture the cognitive process occurring in the human brain. The P&D model determines the driving regimes (e.g., accelerating to increase speed, cruising to maintain speed, braking to stop) and its timing and duration based on the current situation. On the other hand, the action model aims to capture human driving behaviors impacting the state of the vehicle (position, speed, and acceleration) based on Newtonian laws of motion. The action model is bounded by the regimes and conditions computed by the P&D model.

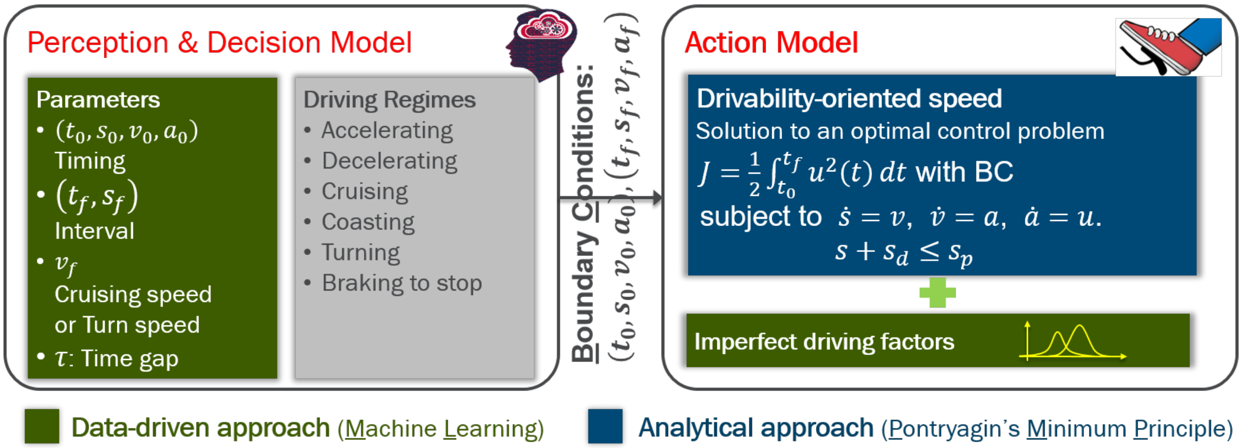


Figure 3-81. Schematic diagram of the human driver model: perception & decision model (left) and action model (right).

The initial focus of this work was the action model development and validation using on-road testing data collected by a highly instrumented vehicle. The assumption that drivers prioritize driving comfort, while avoiding any collisions with the preceding vehicle and obeying traffic rules, leads to the formulation of human driving as an optimal control problem minimizing jerk (the derivative of acceleration) using the vehicle longitudinal dynamics model of the triple integrator. Deriving analytical optimal solutions by employing optimal control theory enables the efficient computation of vehicle state trajectories, and adding the state constraint imposed by the vehicle in front can describe car-following features that depend on the actions of the preceding vehicle.

Data was collected from a highly instrumented vehicle — driven by a human driver and equipped with a dash video camera, GPS tracker, and radar — and then processed to make the data usable for validation, as shown in Figure 3-82. The goal was to collect information about the surrounding environment affecting the driving, such as type of road, speed limits, surrounding vehicles, and intersection controls. The radar detects up to 13 surrounding objects (e.g., oncoming vehicles, surrounding vehicles) simultaneously, both in longitudinal and lateral positions. However, this data needs be filtered to isolate the signal corresponding to the state of the preceding vehicle and to validate car-following scenarios. The recorded geographical coordinates are "map-matched" with HERE maps[139], to augment the recorded data with road attributes such as speed limit, road type, position of traffic lights, etc. A machine-vision algorithm powered by deep learning helps retrieve information about traffic signal states from the image data recorded by dashcam videos. Finally, in order to crosscheck the post-processed data, a visualization tool linking the various data sources was developed.

Figure 3-82. Post-processing of raw on-road testing data for human driver validation.

The vehicle trajectories in the post-processed data were clustered into four distinct driving regimes: accelerating, cruising, coasting, and braking. Assuming a perfect P&D model, the information required by the action model (i.e., boundary conditions) was extracted for each driving regime.

The action part of the human driver model was then developed and implemented in RoadRunner. Information from the experimental data such as speed limit, location of other cars, and location of intersections is then used to set the stage to test the human-driver model. Results for 27 segments between two intersections demonstrate that trajectories generated by the action model of the human driver using this information matched well with those of experimental data, as shown in Figure 3-83.

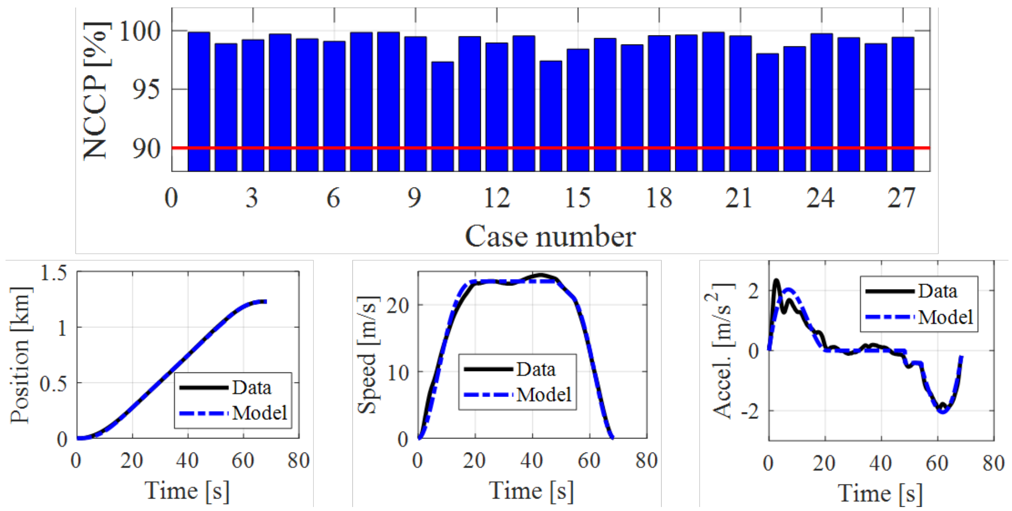


Figure 3-83. Normalized cross correlation power (NCCP) between experimental and simulation data for 27 segments (top) and example for one sample (bottom).

3.4.1.2 *Optimal control theory applied to the eco-driving problem*

- An eco-driving algorithm that smooths vehicle speed ("speed-only") was developed; the algorithm is computationally fast and works with any powertrain.
- An eco-driving algorithm that minimizes the energy consumption of the vehicle by acting on its speed and on its powertrain ("speed+powertrain") was developed for a conventional vehicle, electric vehicle, and hybrid-electric vehicle, and is designed to provide maximum energy savings.

Energy consumption related to a vehicle takes place in three stages: "well-to-tank," "tank-to-wheel," and "wheel-to-miles" (the way the vehicle drives for a given route). The eco-driving problem is related to the "wheel-to-miles" stage and aims at minimizing the vehicle kinetic energy. There is, however, opportunity for additional savings if the "tank-to-wheel" aspect, i.e. the on-board energy efficiency, is considered as well. Two eco-driving control strategies were developed: the speed-only eco-driving optimization focuses mostly on the "wheel-to-miles" stage, while the speed+powertrain eco-driving optimization considers the "tank-to-wheel" and "wheel-to-miles" stages as a compound problem.

In both cases, eco-driving is formulated as an optimal control problem (OCP): The goal is to minimize an energy-related cost function by acting on the commands of a dynamic system, subject to stated constraints imposed by speed limits, the preceding vehicle and intersections. This is summarized in Table 3-10. When solving the OCP, the constraints and boundary conditions are assumed to be known and fixed and form the future horizon (i.e., future time/position interval). Section 3.4.1.3 will detail how these theoretical solutions are applied to perform in a real-time controller that can be evaluated in RoadRunner.

Table 3-10. Optimal control problem formulation for the speed-only and speed+powertrain eco-driving algorithms (see Table 6-5 for a version with equations).

<table>
<tr><th colspan="2">Optimization</th><th>Speed-only</th><th colspan="3">Speed + powertrain</th></tr>
<tr><td colspan="2">Powertrain</td><td>Any</td><td>EV</td><td>ICEV</td><td>HEV</td></tr>
<tr><td colspan="2" rowspan="2">Control variables</td><td rowspan="2">Acceleration</td><td colspan="3">Gear shifting and braking force</td></tr>
<tr><td>Motor torque</td><td>Engine torque</td><td>Motor + engine torque</td></tr>
<tr><td colspan="2">Cost function to minimize</td><td>Acceleration “energy”</td><td>Battery energy</td><td>Fuel mass</td><td>Equivalent energy consumption</td></tr>
<tr><td rowspan="4">subject to</td><td>System dynamics</td><td>Vehicle dynamics</td><td colspan="3">Vehicle dynamics including powertrain operation</td></tr>
<tr><td rowspan="2">State constraints</td><td colspan="4">Preceding vehicle</td></tr>
<tr><td colspan="4">Speed limits</td></tr>
<tr><td>Interior-point constraints</td><td colspan="4">Traffic signal phase and timing (SPaT) (when V2I enabled)</td></tr>
<tr><td colspan="2">Boundary conditions</td><td colspan="4">Final position and final speed given initial position and initial speed</td></tr>
</table>

3.4.1.2.1 Speed-only Eco-Driving

In the speed-only eco-driving strategy, the command is the vehicle acceleration, and the vehicle longitudinal dynamics model is a double integrator linking position, speed, and acceleration. The cost function to minimize is the acceleration energy (the sum of the acceleration squared). This simple formulation allows the control problem to be solved by derivation of analytical closed-form optimal solutions that are functions of the boundary conditions. The resulting acceleration is a piecewise linear function of time. No numerical solvers are required, making this algorithm computationally efficient. Moreover, this control can be applied to all types of vehicles, regardless of powertrain type.

As shown in Figure 3-84, the connected and automated vehicle (CAV) can eco-accelerate from a stop to reach the desired cruising speed (Eco-Acceleration ①). Then, the CAV maintains the desired cruising speed (Eco-Cruising ②). It can decrease or increase the speed following changes in speed limits (Eco-Deceleration ③ or Eco-Acceleration ①). When approaching signalized intersections, the CAV equipped with V2I communication receives information about signal phase and timing (SPaT) from the traffic signal and uses it to plan and follow future speed so that it can pass the next traffic signal on the green phase without unnecessary stops (Eco-Approach ④). Finally, the CAV can decelerate to a complete stop when arriving at stop signs (Eco-Arrival ⑤).

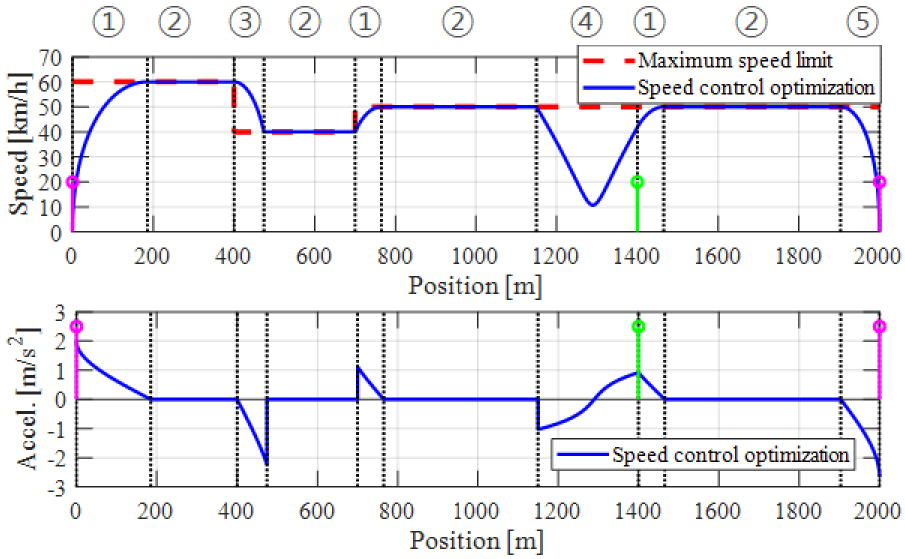


Figure 3-84. Speed (top) and acceleration (bottom) trajectory of speed control optimization for a simple scenario where there are two stops (vertical magenta lines) and one traffic signal (vertical green line). Red dotted line is the varying maximum speed limit.

3.4.1.2.2 Speed+Powertrain Eco-Driving

For the *speed+powertrain* strategy[140,141,142], the objective of the control is the explicit minimization of the energy consumption: either fuel, electricity or a combination of both (see Table 3-10). Direct control of the powertrain components, such as engine torque and gear for a conventional vehicle, allows for the discovery of the most energy-efficient operation areas. In addition to incorporating the efficiency map of powertrain components, the powertrain-aware eco-driving control has a better understanding of kinetic energy recuperation through regenerative braking, due to its detailed modeling of the powertrain.

As the problem is much more complex than in the speed-only eco-driving case, a closed-form analytical solution (i.e., a "formula" giving the solution as a function of time) cannot be formulated. Instead, optimal control theory reduces the global problem to a local problem, at each step combining minimization and a dynamic equation, while still making the algorithm implementable on real-time hardware control units.

In the absence of other vehicles and traffic light intersections, the algorithm creates the state and command trajectory for the entire horizon, and follows these steps, as shown in the left part of Figure 3-85:

1. Split the trip into constant grade and constant speed limit segments (Figure 3-85 a).
2. Adjust steady-state speed (v_{ss}^{*}) for each route segment based on varying road grades and speed limits according to the general target cruising speed (v_{set}^{*})(i.e., a desired travel speed set by the driver) (Figure 3-85 b).
3. Develop solution trajectories of acceleration, deceleration and constant speed between junction points (Figure 3-85 d).
4. Calculate junction speeds at borders of route segments relying on the continuity condition derived from optimal control theory (Figure 3-85 b).
5. Form the speed transition curves in the route segments and connect them together (Figure 3-85 c)

In order to deal with various road and traffic situations in the real world, the algorithm needs to be augmented to comply with constraint conditions. When V2I is enabled and SPaT is available, the target cruising speed (v_{set}^{*}) at the approach of a traffic light is adjusted to optimize the crossing time to avoid stopping and to pass at the green phase (Figure 3-85 e). In the presence of a preceding vehicle, the steady-state speed is set to avoid a collision in the predicted trajectory of the front vehicle (Figure 3-85 f). The workflow of the algorithm to find (v^*_{set}) is summarized in the right part of Figure 3-85.

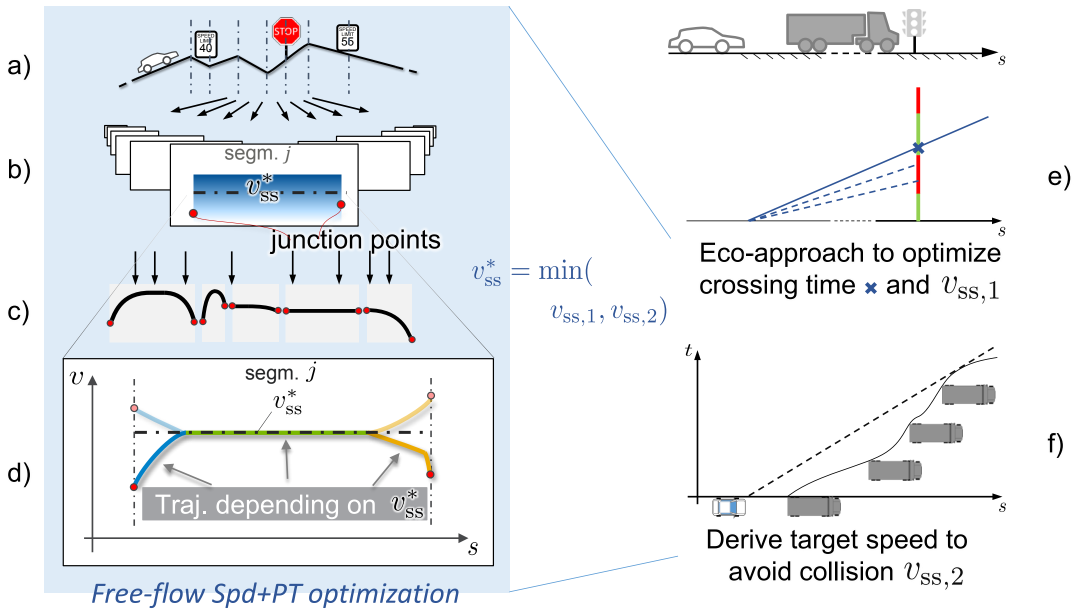


Figure 3-85. The speed+powertrain eco-driving algorithm combines eco-approach to connected traffic lights, collision avoidance, and free-flow optimization.

3.4.1.3 Implementable Real-Time Control

- A model predictive control concept for eco-driving was developed and integrated into controllers within RoadRunner, allowing implementation of the speed-only and speed+powertrain algorithms.
- This setup ensures that the eco-driving algorithms can work in real-world systems with uncertainties, perturbations, and dynamics.

The algorithms described above provide a way to compute the optimal trajectory of commands and states for a given known horizon. There are, however, several barriers to real-world implementation in real-time controllers on actual vehicles. The optimization relies on accurate knowledge about the future driving conditions — the horizon, which comes from various sources: digital maps (road attributes), sensors (other vehicles) or V2X communications (future states of road or vehicle controls). There are many limitations in how far and how accurately the vehicle can “see” into the future. In particular, it is not possible to predict with certainty the behavior of preceding vehicles, especially if they are human-driven. In addition, the models used for optimization are simplified, and there are many software and physical layers between a command and its execution. A result, the vehicle does not respond exactly as the optimization thought it would. To overcome these barriers and make the optimal controllers discussed in Section 3.4.1.2 implementable in the real world, a model-predictive control (MPC) approach is adopted. MPC control theory is based on the iterative, finite-horizon optimization of a plant model towards a specific objective function within a set of additional constraints. Controls are calculated for optimal results over the finite-horizon, yet only the controls for the current time-step are implemented and the controls are then again optimized. By comprehending future outcomes via the finite horizon, MPC has shown improved performance for a range of systems, particularly those that include large time-delays and more complex dynamics.[143]

3.4.1.3.1 Concept of Model Predictive Control for a CAV Controller

Optimal controllers are implemented within a predictive framework with a receding horizon.[144] At each time step, the optimization algorithms solve the eco-driving problem over an entire finite horizon (e.g., 250 m), but only apply the first step of the solution. At the following time/distance step or event-based trigger (such as a change in speed limit), the horizon window moves one step further and the optimization is performed again, thus creating a feedback loop that is critical to the stability of the system. Figure 3-86 illustrates the concept of the receding horizon.

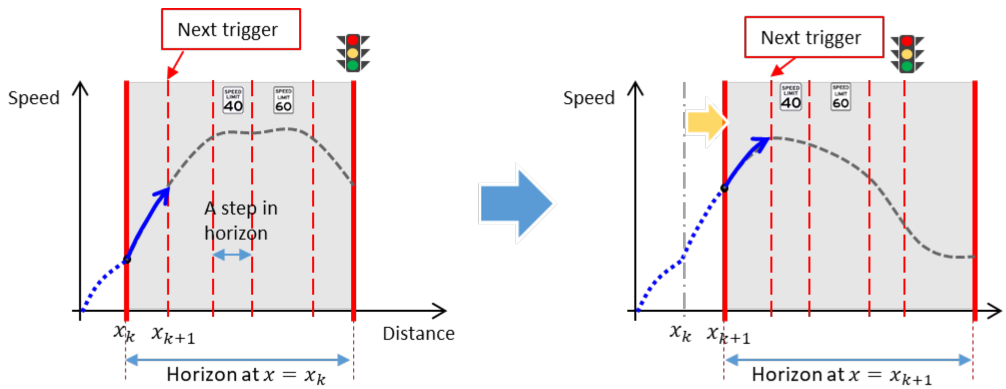


Figure 3-86. Concept of receding horizon: The prediction window at position x_k (left) advances at the following step, x_{k+1} (right).

The CAV controller, shown in Figure 3-87, includes a *horizon generator* that combines the various signals from the perception and sensing block (representing different data sources, such as sensors and machine vision) into a receding horizon. The *speed and powertrain control* block computes the powertrain commands (engine/motor torques, gear, friction brake, and clutch) executed within the *vehicle model*, which then provides a feedback of the resulting vehicle states back to the controller.

The speed and powertrain control block has a different structure depending on whether it is a speed-only (Figure 3-88) or speed+ powertrain (Figure 3-89) implementation of eco-driving. Both types, however, include a reference generator that outputs the ideal state and command trajectories, using one of the optimization algorithms from Section 3.4.1.3.2 or 3.4.1.3.3, and a tracking controller that adjusts for modeling errors and perturbations.

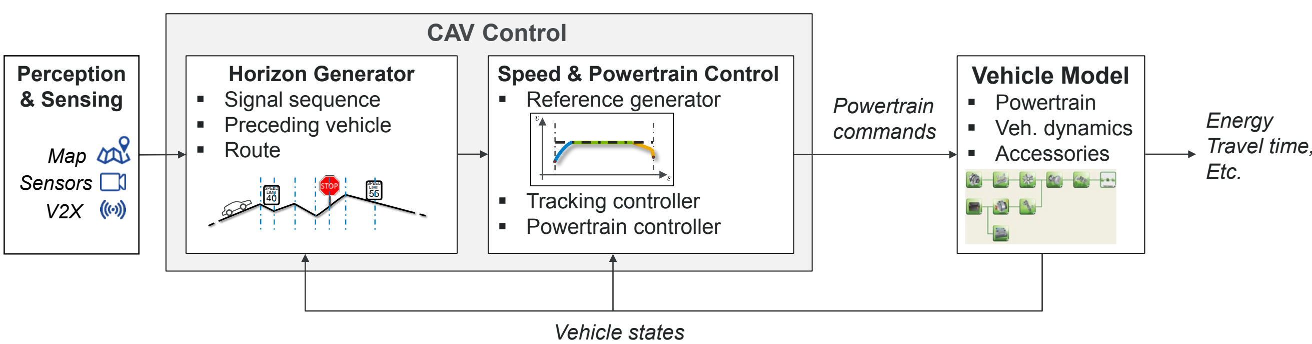


Figure 3-87. Architecture of the CAV controller.

3.4.1.3.2 Implementation of Speed-Only Optimization

In the speed-only eco-driving strategy (Figure 3-88), the *reference generator* (i.e., the eco-driving speed-only algorithm) computes the optimal acceleration and speed trajectories over the horizon. The preceding vehicles, if any, are assumed to maintain their current acceleration over that horizon. The speed trajectory from the reference generator is then fed into a *PID*[iv] *tracking controller,* which converts this command to pedal position. The pedal position is then the input to the baseline Autonomie supervisory powertrain controller, which is not optimized. Thanks to the analytical formulation of the optimal eco-driving solution, this loop can be executed at every clock step.

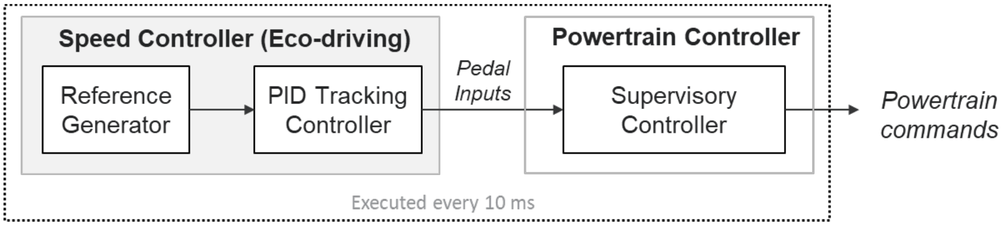


Figure 3-88. Speed and powertrain control architecture in the speed-only eco-driving case.

3.4.1.3.3 Implementation of Speed+Powertrain Optimization

In the case of the speed+powertrain optimization, the optimization algorithm is more computationally demanding. As a result, there are two steps in the optimization, as shown in Figure 3-89. In the receding horizon, a 250 m preview of the road grade and next intersection information are collected. If a front vehicle exists within the preview horizon, its behavior is predicted via an intelligent driver model (IDM).[145] The *reference generator* (i.e., the eco-driving speed+powertrain algorithm) solves the optimal control for the horizon, generating reference trajectories for speed and position, as well as optimal intermediate parameters used in the optimization. A second real-time stage is executed more frequently and combines computation of the optimal commands (*PMP feedforward controller*) for powertrain components such as engine, motor, and brake on the one hand, and tracking of the speed (*PID tracking controller*) for correcting for perturbation and errors on the other hand.

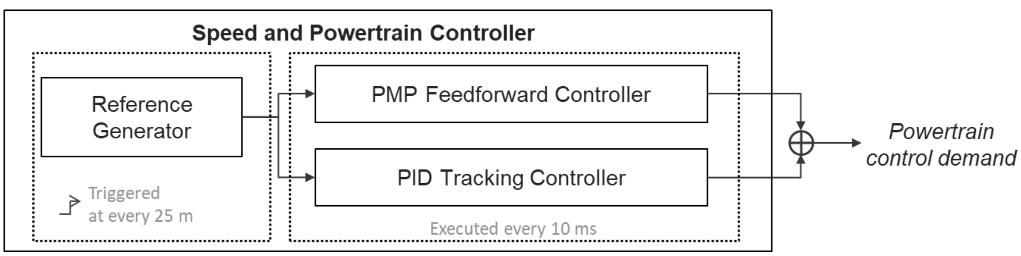


Figure 3-89. Speed and powertrain control architecture in the speed + powertrain eco-driving case.

3.4.1.4 Large Scale Case Study Results

An unprecedented large-scale study was carried out to evaluate the energy impacts of various eco-driving algorithms in a broad range of driving conditions, powertrains, and technology time frames. The results include the following insights:

- Eco-driving saves more in city driving (up to 22%) than in highway driving (up to 6%)
- Speed+powertrain eco-driving typically saves more than the speed-only eco-driving — between 4 and 9 percentage points more for most of the cases in the large-scale study — by considering the best operating points in the powertrain.
- V2I-enabled traffic light eco-approaches often increases eco-driving energy savings, especially for the speed-only eco-driving (up to 10 percentage points increase).
- Speed-only eco-driving *with* V2I saves more than speed+powertrain *without* V2I for EV and conventional powertrains in urban and suburban conditions.

[iv] PID: proportional-integral-derivative controller, a widely used control loop mechanism

- While energy savings are greater for the lead vehicle than for the following vehicle, non-equipped vehicles can also experience up to an 8% energy savings when following a vehicle equipped with eco-driving.
- U.S. Department of Energy Vehicle Technologies Office advance technology targets for engine efficiency improvements at low loads will lead to higher energy savings from eco-driving than from business-as-usual technology improvements for conventional vehicles in future technology scenarios — up to 6 extra percentage points in the 2025 target.

The energy benefits of eco-driving strategies for a midsize car, and for a variety of driving scenarios and powertrain technologies, were evaluated in a large-scale study with over 4,000 simulations, summarized in Table 3-11.. Each simulation includes two vehicles, one following the other. One or both vehicles feature an advanced control while the other uses the baseline control — the realistic, data-driven human driver model described in Section 3.4.1.1.3. Each control has two versions, with or without vehicle-to-infrastructure (V2I) connectivity. With V2I, the vehicle receives signal phase and timing (SPaT) information, which it uses for "eco-approach and departure" to avoid idling at red lights. The "baseline with V2I" corresponds to a "better" driver who can perfectly follow an eco-approach speed recommendation and drives at perfectly constant speed during cruise segments, but otherwise shares the algorithm of the baseline (without V2I) driver.

Each vehicle includes the Autonomie powertrain model corresponding to a vehicle created for the SMART Modeling Workflow (refer to the SMART Mobility Modeling Workflow Capstone Report – Section 3 Common Scenarios and Assumptions). Two powertrain technology scenarios were examined, both for a mid-size car: current technology and short-term future with U.S. Department of Energy Vehicle Technologies Office targets.

Table 3-11. Summary of the main variables in the eco-driving case study.

Variable/Parameter	Description
Powertrain (PT)	• Conventional: powered by an internal combustion engine • HEV: parallel pre-transmission hybrid electric • BEV: battery electric vehicle with 200-mile range
PT technology scenario	• Current technology • Short-term future technology: better engine/motor efficiency, lighter battery, etc.
Control	• Baseline: no optimization • Speed-only eco-driving (EcoDrv Spd/Accel) • Speed+powertrain eco-driving (EcoDrv PT+Spd)
Connectivity	• No vehicle-to-infrastructure (V2I) information: Vehicle does not receive any information from the outside. • V2I: Vehicle receives information about signal phase and timing.
Scenario	Two vehicles, one following the other
Routes	Real-world routes extracted from HERE maps: 16 highway, 9 suburban, 9 urban, 10 mixed (combining all road types)

Figure 3-90 shows the speed profiles for various driving control strategies for the same example route for a BEV. All three controllers with V2I connectivity have information about the current and future state of the second traffic light (at 1670 meters), and slow down before the light so as not to stop and idle, unlike the baseline case without V2I, which has to stop. The two vehicles with eco-driving controllers have smoother speeds than the two baseline controllers.

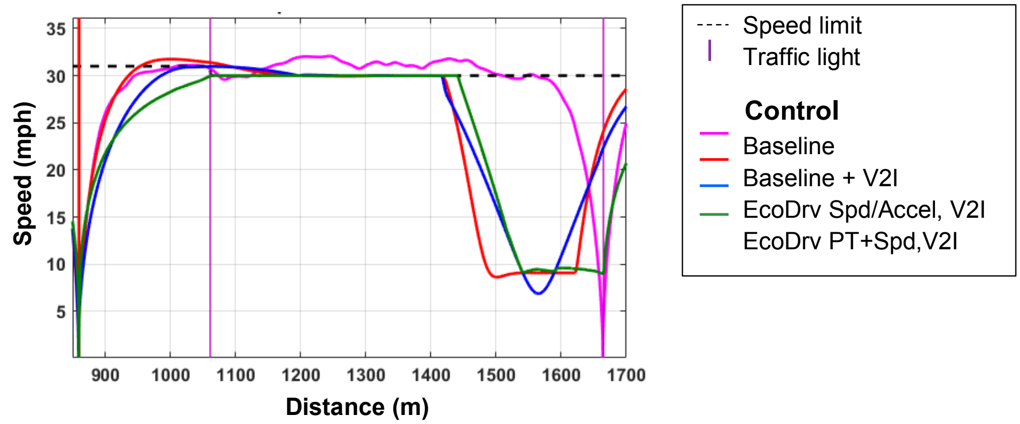


Figure 3-90. Speed traces for a BEV with different control strategies on a short segment with traffic light at 1,670 m.

All simulations include two vehicles, one following the other, with zero, one, or two vehicles with an optimized control rather than the baseline. Figure 3-91 shows four combinations of interest for analysis. First, an optimized vehicle is compared to a baseline vehicle in the lead position that has no other preceding vehicle. In the second and third cases, the optimized vehicle is still compared with the baseline, but in both cases, it is following a lead vehicle that is either a baseline (second case) or an optimized one (third case). Finally, it is also interesting to compare the effect of the control on non-equipped vehicles by comparing two baseline vehicles following either an optimized or a baseline vehicle.

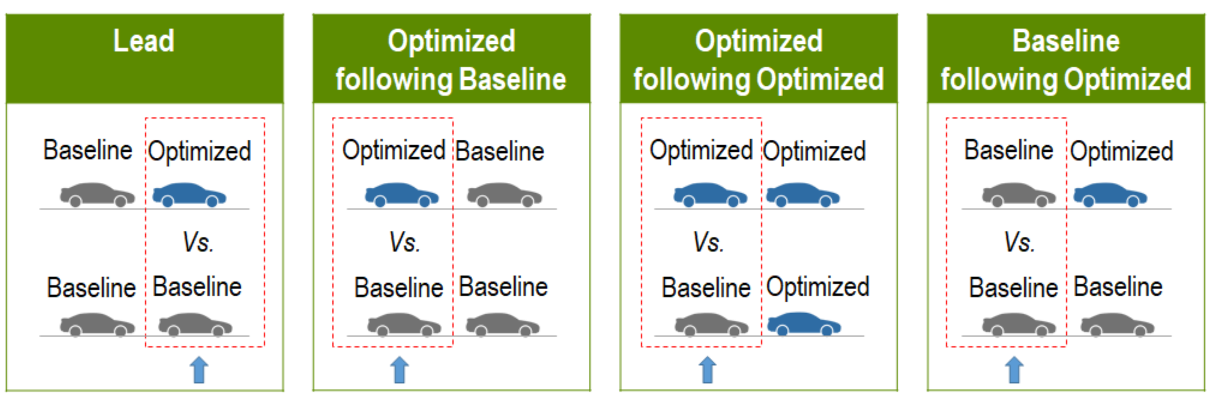


Figure 3-91. Description of the four comparison cases.

In Figure 3-92, the focus of the analysis is on one type of vehicle (HEV) and one type of control (speed+powertrain eco-driving, no V2I) to focus on the position and equipment level. The trends presented here generally hold for other powertrains and controls as well, with changing magnitudes. Eco-driving leads to the greatest energy savings for the lead vehicle in all four cases considered, saving more in urban conditions (18%) than in highway driving (6%,) because there are more acceleration/deceleration cycles in city driving that eco-driving can optimize. When the eco-driving vehicle is following another vehicle, the savings are lower (12%–14% in urban driving) because the preceding vehicle adds constraints to the control problem. As there is no vehicle-to-vehicle connectivity, the eco-driving vehicle cannot anticipate the preceding vehicle's movements and must occasionally brake to avoid collisions, as does the non-optimized vehicle in the same position. Finally, non-equipped vehicles are either essentially not affected or actually save energy when the preceding vehicle is equipped with eco-driving (3.6% in highway conditions). This suggests beneficial impacts of eco-driving even at partial penetrations.

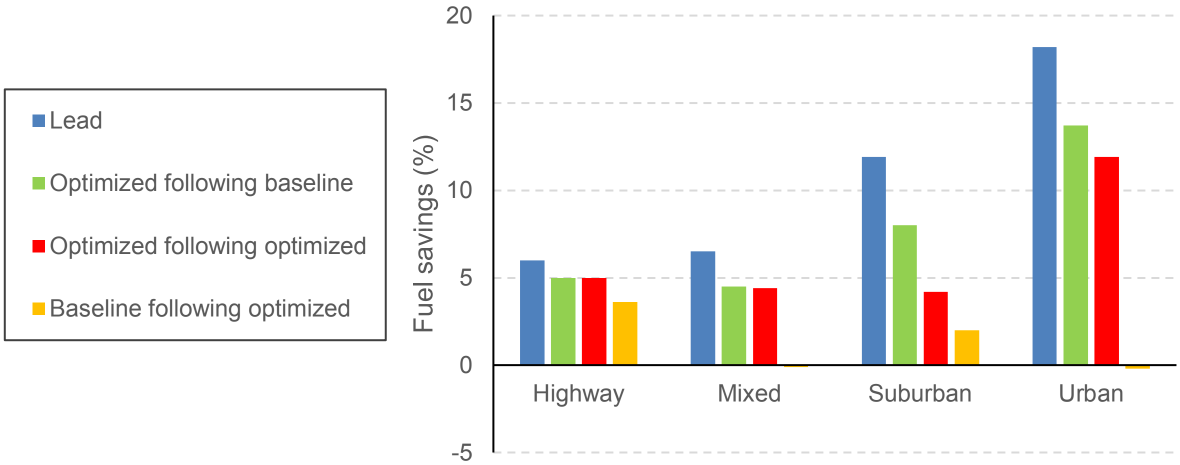


Figure 3-92. Fuel savings for the HEV (current technology) with speed+powertrain eco-driving and no V2I in various scenarios.

When comparing all types of controllers for the lead vehicle (Figure 3-93), it appears that speed+powertrain eco-driving with V2I generally shows the highest energy savings (22% for conventional, urban). The savings for the conventional and the HEV vehicles are comparable, but are lower for the EV — 10% at most.

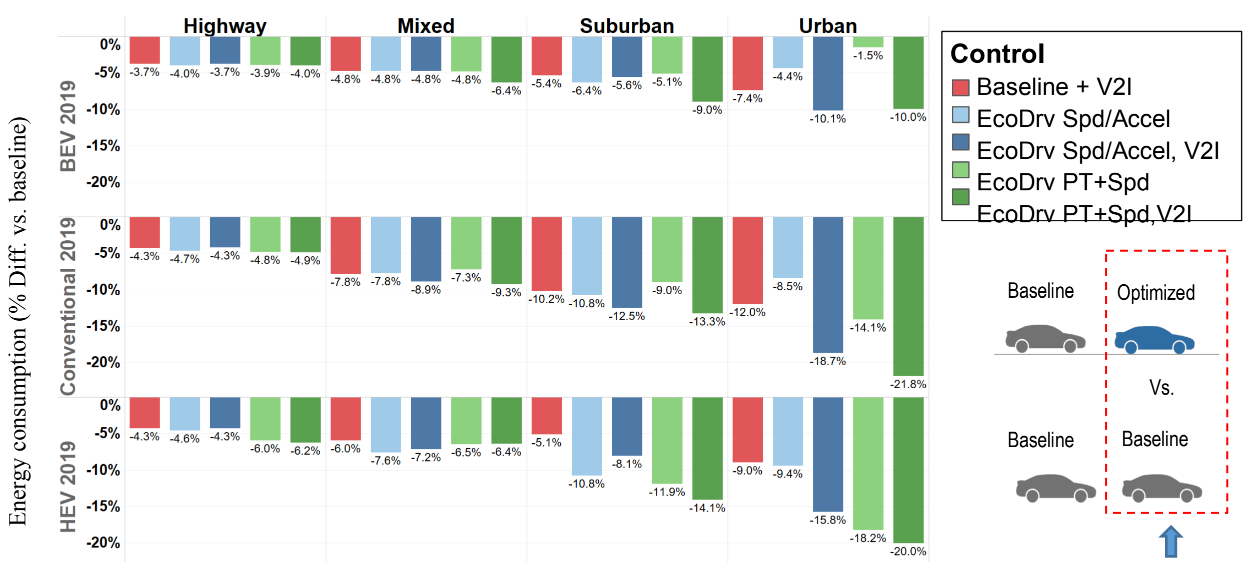


Figure 3-93. Energy consumption savings compared to baseline control for a vehicle in the lead position, with current powertrain technology, for various powertrains.[v]

[v] A negative number means energy savings

3.4.1.4.1 Impact of Connectivity

V2I connectivity allows vehicles to receive SPaT information and use it to cross a traffic light intersection in its green phase. In the case study, it was assumed that either all traffic lights are connected or none of them are. In urban driving, with large numbers of traffic lights with relatively short distances between them, V2I connectivity brings significant savings. The "baseline with V2I" on urban roads, for example, consumes between 7% and 12% less energy than the baseline vehicle (Figure 3-93). The "baseline with V2I" includes a simple eco-approach algorithm and cruises at constant speed, and the baseline human driver model includes some added noise compared to the "baseline with V2I." V2I connectivity also increases the savings of the eco-driving controllers up to 10 additional percentage points for speed-only eco-driving with V2I (vs. non-V2I) for the conventional powertrain in urban conditions, as shown in Figure 3-94, and up to 7.7% for the speed+powertrain algorithm with the same road type and powertrain. In fact, speed-only eco-driving *with* V2I saves more than speed+powertrain *without* V2I for EV and conventional powertrains in urban and suburban conditions.

There are, however, instances in which the V2I-enabled eco-approach leads to lower savings than the non-V2I case (e.g., HEV in mixed and suburban cases and BEV in the suburban case for the speed-only algorithm; cf. Figure 3-93). In these cases, the controller does not compute truly energy-optimal trajectories, because of its limited "preview" of the future and because the objective of the optimal control in the speed-only case is not the explicit minimization of energy but of acceleration. Secondly, the calibration of the controller, which affects not only energy consumption but also travel time, drivability, safety, etc., was not optimized in this case study. Finally, the non-optimized Autonomie baseline energy management strategy for the HEV may affect the "without V2I" and "with V2I" cases in different ways.

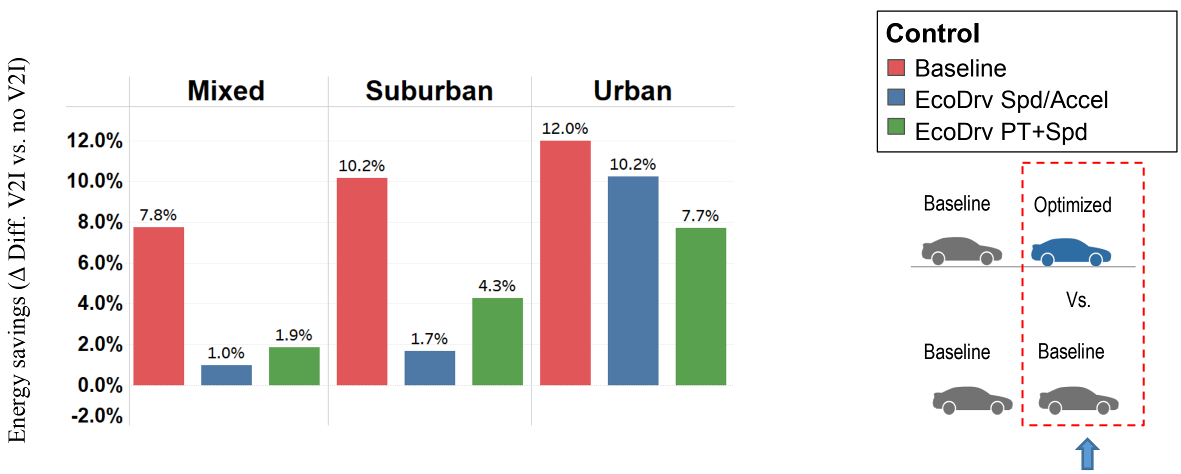


Figure 3-94. Difference in percentage of energy consumption saving between a controller with V2I and the same controller without V2I for a vehicle in lead position, with current conventional powertrain technology.

3.4.1.4.2 Impact of Powertrain Inclusion on Optimization

The addition of powertrain dynamics to the optimization (speed+powertrain vs speed-only) generally leads to greater energy savings, especially in urban scenarios for conventional vehicles and HEVs (3%–6% and 4%–9% additional, respectively), as shown in Figure 3-93. Some of these extra savings are explained by improved component operating conditions.

For example, in the case of the HEV in lead position, engine and motor efficiencies are higher by up to 2 and up to 5 percentage points, respectively, in non-highway scenarios when compared to speed-only eco-driving, as shown in Figure 3-95. This is achieved by adjusting the degrees of freedom, such as vehicle speed, power split, and gear. Gear shifting in particular occurs more often (2.5 times more shifts compared to the baseline).

The calibration of the control can be adjusted to reduce the number of shifts for better driving comfort, but that generally also reduces the energy savings.

The difference in optimization objectives also explains the differences in operations. As shown in Figure 3-96 for one urban driving example, the speed-only strategy uses the engine mostly in the lower torque region because it simply minimizes the acceleration energy. The speed+powertrain strategy, on the other hand, shifts the engine operating points to a higher, more efficient torque region through stronger accelerations. While the stronger accelerations lead to greater component efficiency, they may occasionally result in more undesired braking in the absence of V2I/SPaT information. For example, the speed+powertrain controller will command stronger acceleration to reach cruising speed on the assumption of a green light, but then has to brake when the light turns red. As a result, the speed+powertrain without V2I occasionally performs comparatively worse than the speed-only controller in some non-urban cases (e.g., conventional, suburban, shown in Figure 3-93).

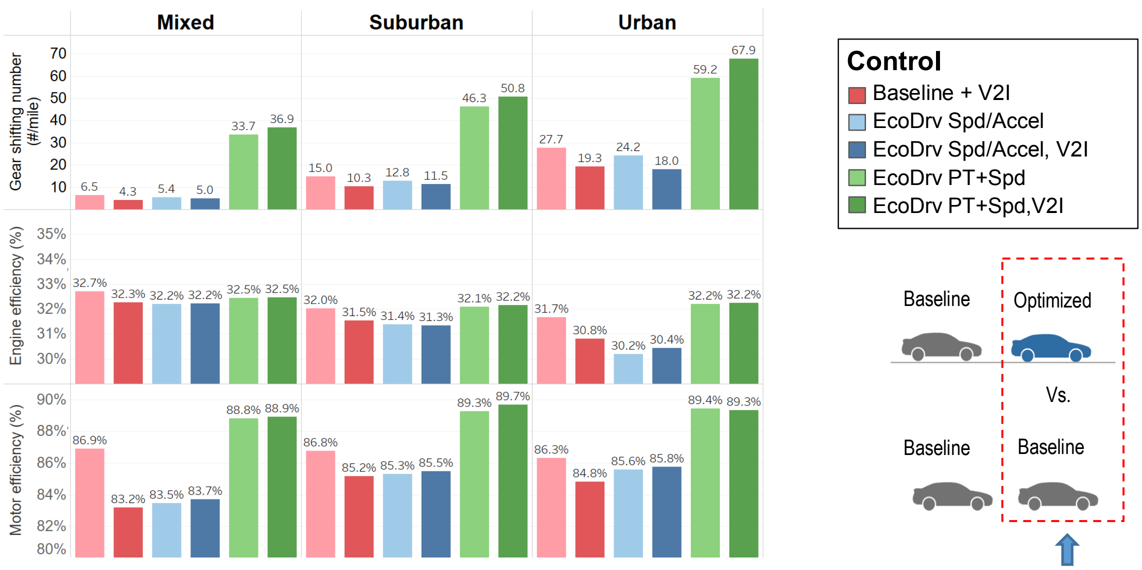


Figure 3-95. Various component operation metrics for the HEV in a lead position (current technology).

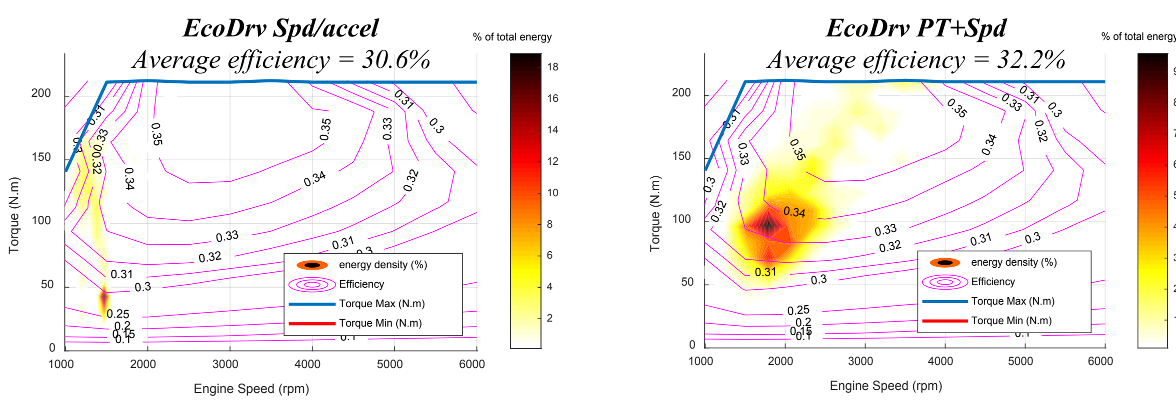


Figure 3-96. Engine operating points (density as a percentage of total energy) for a HEV (current technology) in lead position, for speed-only (left) and speed+powertrain (right) eco-driving strategies in one urban driving example.

3.4.1.4.3 Impact of Powertrain Technology Improvements Scenario

Eco-driving affects energy savings differently depending on the powertrain technology scenario. Figure 3-97. shows the difference in energy consumption savings between the 2025 technology (future) and 2019 technology (current) scenarios. Eco-driving savings are up to 6 percentage points higher for a conventional vehicle in the future technology scenario. One reason is that eco-driving tends to reduce overall tractive effort and thus the engine load, which often leads to lower engine efficiency; the future technology case assumes strong improvements in efficiency in these low-load areas. This is especially true for the speed-only control, in which lower engine loads are most prevalent.

For the BEV, however, relative savings resulting from eco-driving are the same for both technology scenarios. A similar conclusion can be drawn for the HEV, except for the speed+powertrain eco-driving controller: It brings less relative energy saving in future years than in the current scenario compared to the respective baselines. It still brings energy savings compared with the baseline in the same technology scenario, but comparatively less than in the current scenario, because the future baseline it is compared against has already taken advantage of the improved engine efficiency.

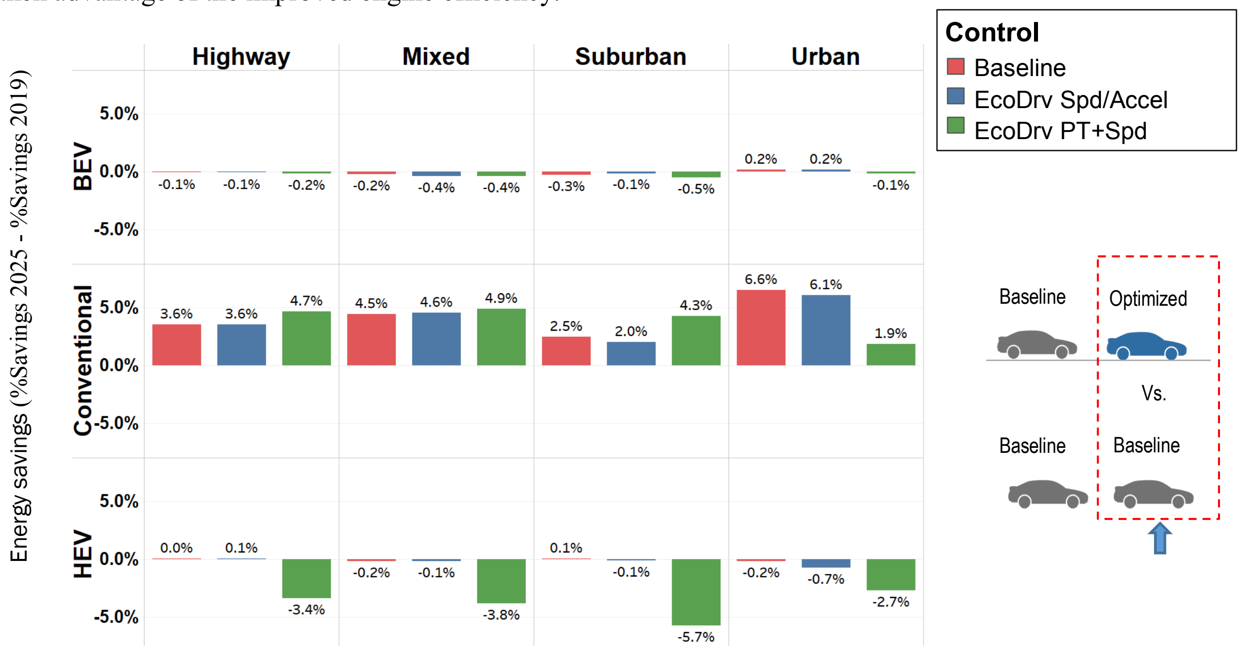


Figure 3-97. Difference in percentage of energy consumption savings between a 2025 and a 2019 vehicle in lead position for various types of controllers. [vi]

3.4.1.4.4 Impact on Non-equipped Vehicles

As suggested earlier for the HEV case (Figure 3-92), eco-driving can also benefit non-equipped vehicles. When a non-optimized baseline vehicle follows a vehicle equipped with eco-driving, as shown in Figure 3-98, it can save up to 8% in energy consumption (conventional vehicle, urban) compared to the baseline. The following vehicle especially benefits from anticipating the driving of the lead vehicle (with V2I) or the “smoother” driving of the lead vehicle. The savings are greater for the conventional vehicle, which always benefits from reduced braking. The speed-only eco-driving strategy is generally better for the following vehicle, as speed+powertrain takes into not only account kinetic energy optimization but also onboard energy management. The non-optimized vehicle following the optimized speed+powertrain vehicle “sees” only a different speed, which may not be beneficial in itself if it is not accompanied by the optimized energy management that the lead vehicle uses.

[vi] $= \%ES^*_{2025} - \%ES^*_{2019} = \left(1 - \frac{EC^*_{2025}}{EC^{baseline}_{2025}}\right) - \left(1 - \frac{EC^*_{2019}}{EC^{baseline}_{2019}}\right)$ where $\%ES_X$ is relative energy savings in year X, and EC_X is the energy consumption in year X; the * refers to the controller of interest (as opposed to the baseline)

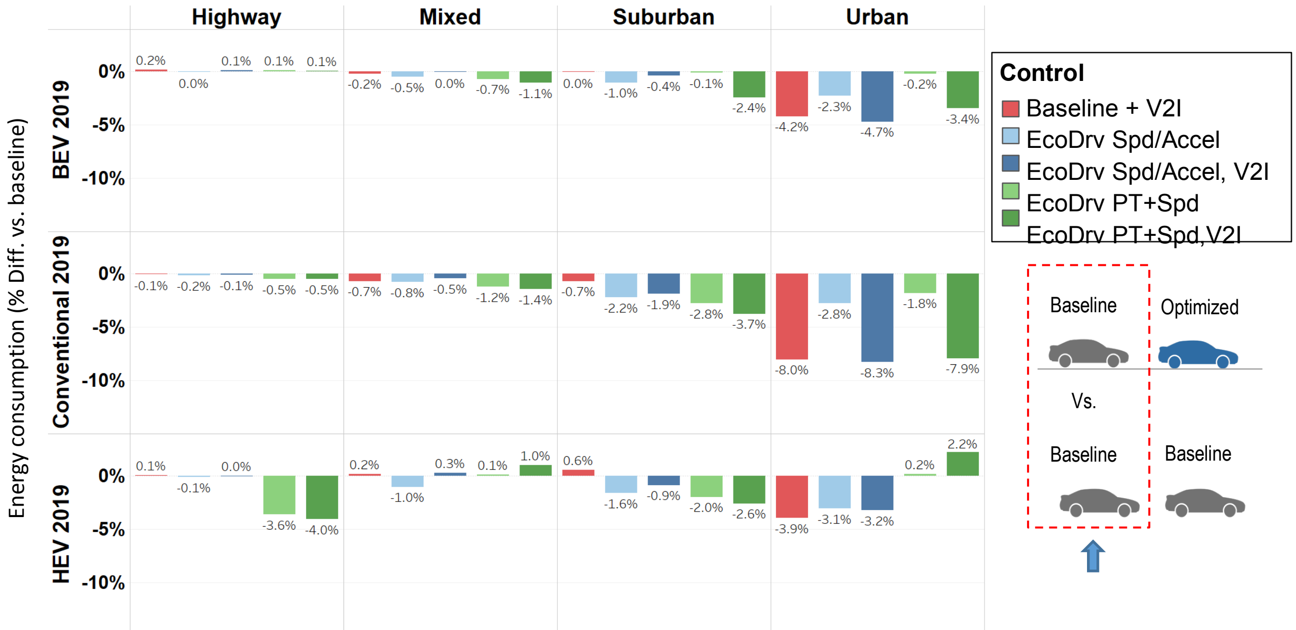


Figure 3-98. Energy consumption of following baseline vehicle (lead: control versus baseline) with current technology and various powertrains

3.4.1.5 Perspective

A common risk of control-driven energy improvement research is to overestimate energy savings by fine-tuning the controls for small sets of scenarios. In this work, this risk was mitigated by integrating robustness to broad ranges of uncontrolled situations in the control design and by using high-fidelity models in a large number of real-world trip scenarios to find representative estimations of the benefits of CAV-enabled eco-driving controls. It should be noted, however, that the results and trends identified in the analysis still include a certain level of uncertainty, originating from multiple sources described below. Suggested future research could further reduce these uncertainties.

Scenario: The benefits of the eco-driving algorithms vary significantly depending on the scenario, the type of route, its topography, the placement and timing of traffic lights, etc. Figure 3-99 shows the distribution of energy savings for one example of powertrain, technology level and road environment. A larger sample of scenarios would reduce the impact of potential outliers.

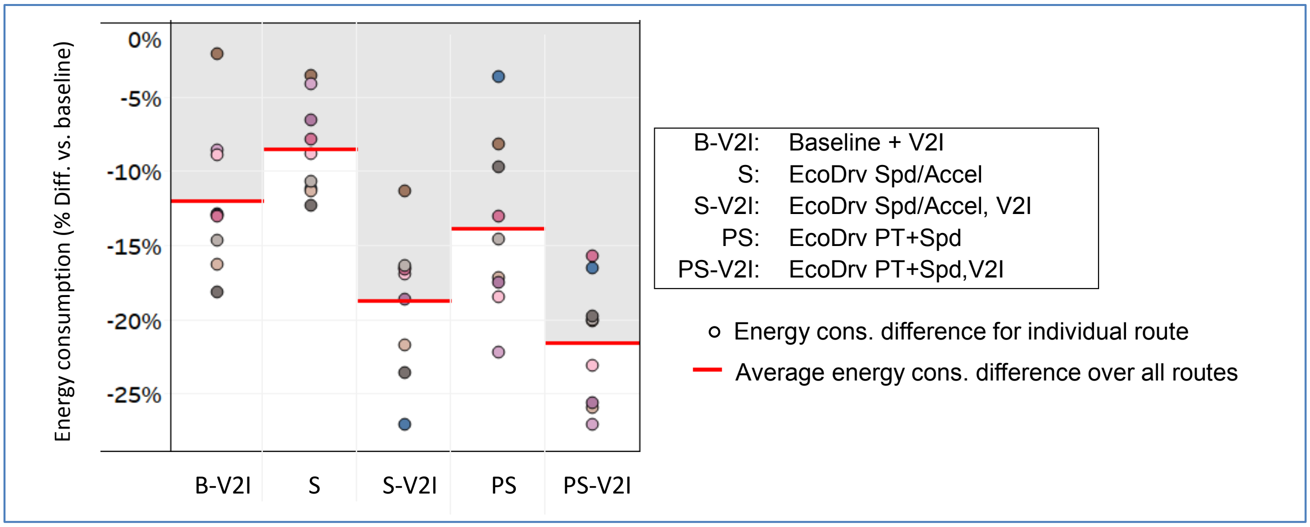


Figure 3-99. Distribution of energy savings for lead vehicle (conventional, current technology, urban scenarios).

Sub-optimality: The eco-driving controllers do not necessarily produce true optimum results, for several reasons. First, knowledge about the future is only partial (even in the case of V2I, knowledge of SPaT is limited to a 250 m range). Deviations between anticipated (e.g., green traffic light) and actual (e.g., red light) predictions can lead to actions (a sudden braking event) that negatively impact energy consumption. Future research could investigate whether better horizon prediction can help mitigate these occurrences.

Calibration: Each eco-driving controller includes calibrations that define constraints (e.g., maximum acceleration rate) or parametrization of controls that are not optimized (e.g., speed tracking). Relative savings can be affected and trends modified by changes in calibration. Further work could include developing calibration optimization methods.

Controller heterogeneity: The controllers that are compared as part of this study are significantly different from each other and were created in parallel development tracks. Because of different levels of complexity, maturity, and "manual" calibration optimization effort, bias in the comparison may exist and may skew the results. In future developments, further maturation of the more complex controllers and common sets of controller-independent metrics could be adopted for consistent calibrations across all controllers to ensure "fair" comparisons.

3.4.1.6 Summary

The work presented in this section has led to several contributions to the study of energy-focused CAV control development. New models were developed and then validated in RoadRunner to simulate not only existing CAV technologies (e.g., ACC) but human driving as well. The latter is important, as it serves as the baseline against which other forms of CAV control are compared. Novel eco-driving controls that leverage connectivity and automation to drive more efficiently were developed — including ones that optimize both the driving dynamics and the powertrain operations — for EVs, conventional engine-powered vehicles and hybrids. These controls were developed with implementation in mind: They are designed to work in a variety of situations (e.g., when following other vehicles), include realistic prediction horizons, and have feedback loops to account for perturbations and model errors.

A large-scale case study demonstrated:

- CAV-enabled eco-driving algorithms can reduce energy use up to 22% when compared to a simulated human baseline.

- Controls that optimize powertrain operation as well as speed generally perform better than controls that focus only on speed.
- Knowledge of traffic light sequences enabled by V2I generally makes eco-driving more beneficial.
- Non-equipped vehicles can also save energy when they follow vehicles equipped with eco-driving controls.

3.4.2 Corridor and Vehicle Level Coordination Strategies

- Simulation showed that ACC vehicles with V2I capability could follow roadside variable speed limit/advisories (VSL/VSA) to maintain a set speed, which could improve traffic throughput or increase TTD (total travel distance) compared to the traffic with 0% ACC and without V2I.
- At a signalized intersection, if an active coordinated traffic signal control is used to integrate the CACC vehicle operation with the signal control, capacity will increase with the market penetration levels of CACC vehicles. At 100% market penetration, this capacity increase is about 75%; fuel consumption in mpg would increase by 70%.
- With partial penetration of CAVs and a heterogeneous fleet (different vehicle classes from light-duty to heavy duty), the optimal coordination framework developed by the CAVs Pillar provided fuel savings of 3% to 30% for a highlighted freeway merging scenario under moderate to heavy traffic.
- At lower CAV penetration levels, in a real-world corridor, the developed coordination framework still achieved a significant overall corridor fuel consumption reduction. For example, at 20% CAV penetration, a fuel consumption reduction of 4% was achieved.

The goals of energy efficient mobility systems are to alleviate congestion, reduce energy use and emissions, and improve safety. At the vehicle and corridor level, core technologies include vehicle connectivity, vehicle automation, and the notion of a cooperative transportation infrastructure enabled by these advanced mobility technologies. Intersections, merging roadways, speed reduction zones, along with the drivers' responses to various disturbances, are currently the primary sources of bottlenecks that contribute to traffic congestion and stop-and-go driving with significant implications in both fuel consumption and traffic stability.[146,147,148,149] In 2017, congestion caused people in urban areas in U.S. to spend 8.8 billion hours more on the road and to purchase an extra 3.3 billion gallons of fuel, resulting in a total cost estimated at $166 billion.[150] Connected and automated vehicles (CAVs) provide a promising opportunity for enabling uses and operators to better monitor transportation network conditions and to improve traffic flow via a range of coordination methods starting with providing improved information to drivers to full automation to better coordinate traffic flows. CAVs can be controlled at different transportation-system levels, e.g., intersections, merging roadways, roundabouts, speed reduction zones, and can assist drivers in making better operating decisions to improve safety and reduce pollution, fuel consumption, and travel delays.

3.4.2.1 Active Traffic Management Strategies for Corridor-Level Traffic Improvements

- Simulation showed that ACC vehicles with V2I capability could follow roadside variable speed limit/advisories (VSL/VSA) to maintain a set speed, which could improve traffic throughput or increase TTD (total travel distance) compared to the traffic with 0% ACC and without V2I.
- For penetrations of about 10-30% of ACC in the simulated corridor:
  - Total travel time (TTT) could be reduced by ~6-7%
  - Speed variation could be reduced by 8%
  - Total delay could be reduced by ~9-11%

These improvements may indicate that even with low penetration of CAVs, benefits in energy saving, emission reduction and safety may be realized with V2I capability.

Section 3.3.1 of this report and several other studies[151,152,153] have indicated that increased ACC market penetration will aggravate traffic and lead to more energy consumption since ACC, as a longitudinal autonomous driving mode, has inferior performance compared to experienced drivers when following other vehicles. There are two reasons for this conclusion: (a) experienced drivers will have a much better perception of and prediction ability for traffic in front of them, which will lead to a shorter time gap, safer performance and reduced cumulative delay, and (b) ACC strings will have cumulative delays from downstream to upstream since there is no V2V between those ACC vehicles. The cumulative delay is detrimental to vehicle safety and driver comfort. Therefore, ACC vehicles usually operate with longer time-gap settings.[154] Adding to the traffic aggravation, the time gaps are usually large so the vehicles can respond in time. Although CAVs (with V2V) can effectively avoid those deficiencies and improve traffic mobility and safety, low market penetration of CAVs will not bring many opportunities for CACC/platooning-capable vehicles to get together for platooning or CACC strings. Therefore, most CAVs will have to be operated in ACC mode until there is a higher penetration of CAVs enabled with CACC.

In this context, the following investigation is intended to improve traffic mobility and safety as well as energy consumption using a V2I type of VSL/VSA. Results showed that although ACC will have longer time gaps between vehicles, which is detrimental to traffic, V2I types of VSL/VSA could compensate for this by increasing overall performance at the system level.

The approach is as follows: an active traffic management (ATM) strategy, VSL, is adopted to optimize the downstream bottleneck flow.[155] It is assumed that all the automated or partially automated vehicles have vehicle-to-infrastructure connection (V2I) but not vehicle-to-vehicle connections. This connection can be implemented with a simple cellular phone API. The cellular phone can connect via the vehicle's Bluetooth® connection. With those connections, the VSL determined by the traffic management center (TMC) can be passed to the vehicle and used as the set-speed of the ACC vehicle. It can also be displayed to the driver, and the driver can follow this set speed based on the actual traffic situation. The determination of the VSL for each road section is achieved by model predictive control (MPC)[156], which utilizes an iterative, finite-horizon optimization of a plant model to optimize the objective function and specify the current control action while remaining cognizant of future outcomes over the finite horizon. For this work, the plant model is based on the speed dynamics of the second order METANET model.[157] The model can be reduced in practice to an in-field implementation. For validation of the algorithm, a well-calibrated Aimsun microscopic traffic simulation model of eastbound I-66 inside the Washington, D.C. Beltway was used as the case study.[158] The road geometry for the study is depicted in Figure 3-100.The design procedure can be divided into the following steps:

Step 1: Divide the freeway network into cells based on section length, number of lanes, on-ramp locations and traffic detector locations

Step 2: Determine the desired speed near the most downstream bottlenecks using a simple regulator feedback control

Step 3: Determine the VSL in other cells using an MPC approach discussed below

It was assumed that all the ACC vehicles had V2I capability in the sense that the VSL determined by the TMC (or roadside) was passed to the ACC vehicles and used as the set speed. The driver behavior of ACC vehicles was excluded. The simulation was run for different market penetration of ACC vehicles: 0%, 10%, 30%, and 50%. Each scenario was run for 10 replications (random seeds).vii All the performance parameters obtained were averaged over the 10 replications. The following parameters are used to evaluate of the performance of the VSL strategy (Figure 3-100):

[vii] The initial flow and demands afterword from the mainline upstream and on-ramp are statistically distributed to verify the robustness of traffic management strategy.

- TTT – total travel time (wish to reduce)
- TTD – total travel distance (wish to increase)
- TD – Total delay (wish to reduce)
- Spd Var – speed variation (wish to reduce)
- Ave # of Stops – average number of stops (wish to reduce)
- Flow@Syc – Flow at onramp merging bottleneck from Sycamore (wish to increase the most downstream bottleneck flow)
- Flow@Merge – Flow at the bottleneck of freeway merge of I-66 EB and VA 267 (this flow may be reduced to some extent to allow downstream to operate at its maximum flow)

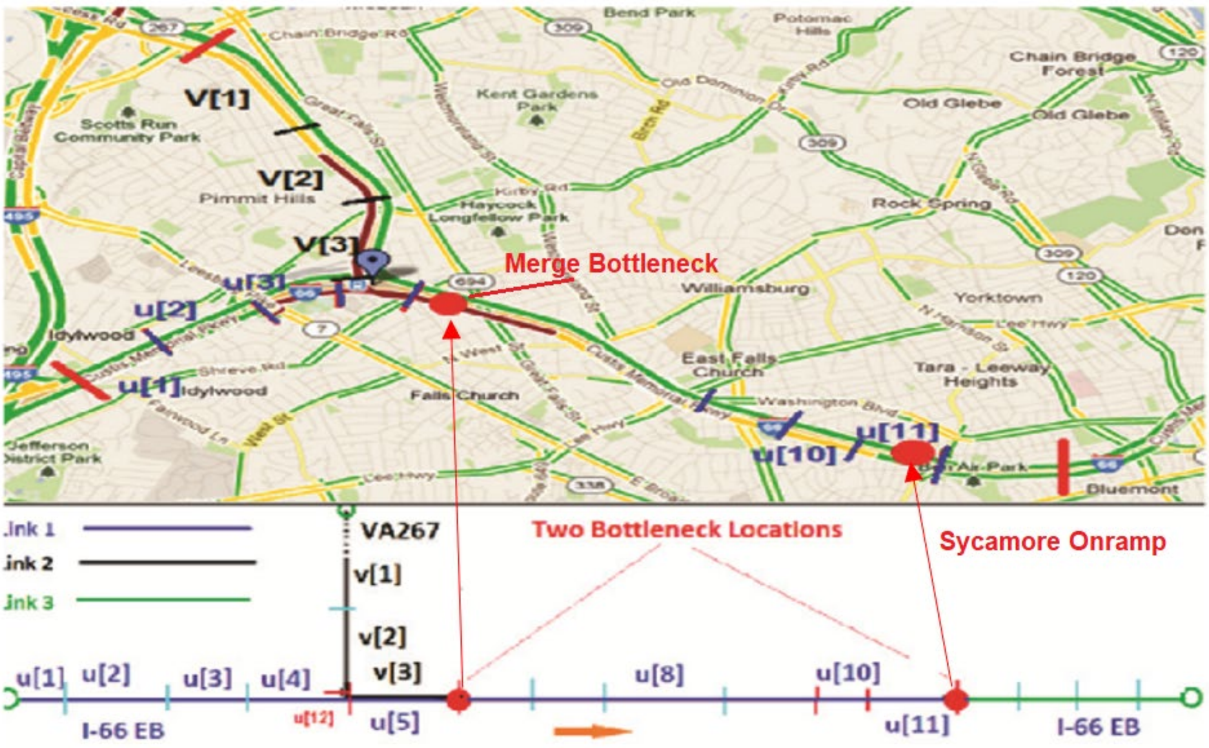


Figure 3-100. Road geometry for microscopic traffic simulation: I-66 EB inside the Beltway, with two bottlenecks marked with red spots.

Table 3-12 shows the percentage changes, compared to baseline traffic, for traffic improvement (green) or worsening (red) with ACC penetration of 10%, 30% and 50%, assuming that all of the ACC vehicles have V2I connections.

Table 3-12. Averaged performance parameter improvements for each penetration level of ACC vehicles over 10 replications (random seeds) market

Market Penetration	TTT (%)	TTD (%)	TD (%)	Spd. Var. (%)	Ave. # of Stops (%)	Flow@Syc. (%)	Flow@ Merge (%)
10%	-6.0	0.8	-9.4	-8.4	-3.5	1.8	-0.2
30%	-7.0	1.3	-11.0	-8.3	-4.2	2.4	-0.1
50%	-8.9	1.4	-13.7	-9.3	-4.9	2.2	-0.1
Mean	-7.3	1.2	-11.4	-8.7	-4.2	2.1	-0.1

It can be observed from the table that an improvement has been achieved in all metrics, even with 10% penetration of ACC vehicles. The most downstream of the two bottlenecks (marked as red spots), the Sycamore on-ramp, is critical. Some minor flow reduction at an upstream freeway merge is necessary to improve the flow at the most downstream bottleneck that determines the throughput of the whole corridor. Note that CACC operation was not assumed here, so the potential benefit is due to the V2I type of VSL only.

This work confirmed the benefits of improving traffic through V2I variable speed limit (VSL) guidance even for relatively low penetrations of ACC or CACC vehicles. This approach uses currently available road traffic detector information and ACC vehicle capabilities (with V2I capability) to calculate a VSL for each small section of the freeway corridor, which is then passed back to the ACC vehicle through V2I and used as the set-speed. Simulation showed that total travel time could be reduced by ~6-7% and speed variation could be reduced by 8% when the penetration of ACC was about ~10-30%. This approach has promise to improve traffic when the penetration of CAVs is low.

3.4.2.2 Active Coordinated Traffic Signal Control for Mixed Traffic at Signalized Intersections

- For signalized urban intersections, simulation results with and without CACC operating through a standard four-way signalized intersection, show a 67% capacity increase for the major approach and a 49% capacity increase for the minor approach when the CACC market penetration increases from 0% to 100%. While this throughput increase is generally a positive development it is not necessarily optimal. In higher CACC market penetration cases the CACC string may prevent a vehicle needing to switch lanes or turn to find a gap upstream from the intersection and thus the vehicle is forced to make aggressive last-minute lane changes near the intersection leading to an interruption in queue discharge flow.
- At a signalized intersection, if an active coordinated traffic signal control is used to integrate the CACC vehicle operation with the signal control, capacity will increase with the market penetration levels of CACC vehicles. At 100% market penetration, this capacity increase is about 75%; fuel consumption in mpg would increase by 70%.

The microsimulation vehicle-following model for CAVs described above was also used to identify the effects of CACC on urban signalized intersections, using the VT-Micro model for energy consumption evaluation. The simulation depicted the performance of a four-way signalized intersection with and without CACC and a cooperative signal control algorithm.[159] The test intersection had a major southbound/northbound approach and a minor westbound/eastbound approach. The major approach had two through lanes and a dedicated left turn lane, while the minor approach had one through lane and one left turn lane. The major approach traffic was 95% through movement and 5% left turn movement, while the traffic in the minor approach was 45% left turn, 45% right turn, and 10% through movement. The baseline simulation was performed with 0% CACC vehicles. The intersection's signal was controlled by a typical actuated signal controller. In addition to the baseline simulation, scenarios of 20%, 40%, 60%, 80%, and 100% CACC market penetration with and without the cooperative signal controller were analyzed.

The intersection capacity at various CACC penetrations is shown in Figure 3-101. The data were collected without activating the cooperative signal controller. The results therefore depict the isolated impact of CACC. There was a 67% capacity increase for the major approach and a 49% increase for the minor approach when the CACC market penetration increased from 0% to 100%. The capacity of the major approach was substantially larger than the minor approach because the major approach had more lanes and was assigned a longer maximum green time. For the major approach, the capacity first increased quadratically as the CACC market penetration changed from 0% to 40%. After that, the increase followed a linear trend.

The rate of increase no longer follows the quadratic trend because of the influence of lane-changing behaviors that occurred near the intersection stop bar (stop line). When a vehicle needs to make a left turn at the intersection, it makes mandatory lane changes towards the left turn lane. In higher CACC market penetration cases, where the CACC string operation may prevent that vehicle from finding a gap upstream of the intersection, the lane-changing vehicle was often forced to make aggressive last-minute lane changes near the intersection. This would greatly interrupt the queue discharging flow (the flow at the immediate downstream section of the intersection) of the CACC strings. As a result, the capacity benefit that could have been provided by the CACC string operation was substantially decreased. It can be observed that the minor approach movement did not have capacity increases when the CACC penetration level was 20% or lower. It started to increase only when the CACC penetration was over 40%. This was partially because the traffic on the minor approach was weighted less than the major approach in the overall traffic throughput optimization and partially because a CACC-capable vehicle would likely drive in ACC mode for low CACC penetrations.

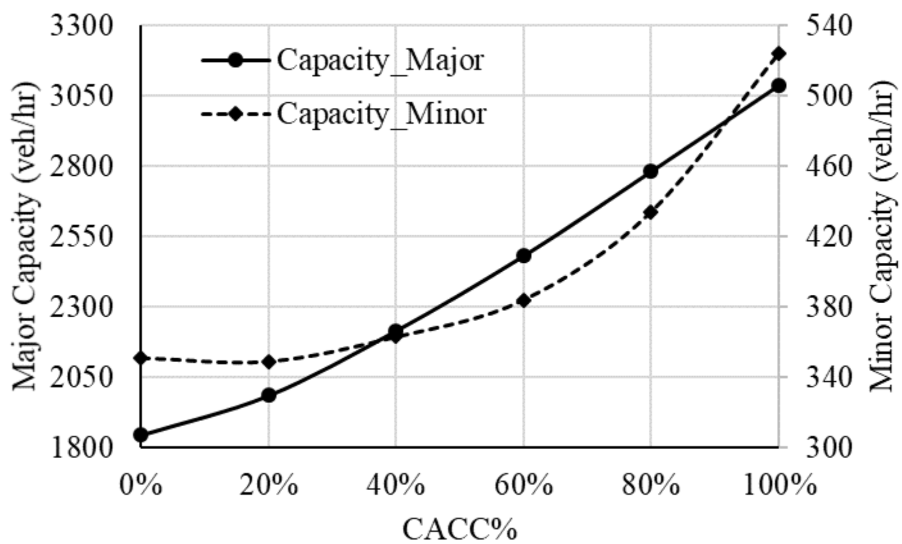


Figure 3-101. Capacity impact of CACC on an urban signalized intersection without a cooperative signal controller.

The influence of the cooperative signal control algorithm developed by the CAV Pillar was investigated under various CACC market penetrations as well. In the simulation runs, the traffic demand input for the major approach in the 0% CACC case was 1,800 vehicles per hour, and the demand for the minor approach was 350 vehicles per hour. Average vehicle fuel efficiency (mpg) was used to depict the effects of the algorithm on both the traffic flow and vehicle fuel consumption.

Vehicle speed and fuel efficiency variations by CACC market penetration levels are shown in Figure 3-102 and Figure 3-103. The results showed that the proposed cooperative signal control algorithm could assign green light time more efficiently than the default actuated controller. Consequently, the queued vehicles could be released from the intersection within a control cycle even in cases with 20% or lower CACC vehicles. For this reason, the algorithm brought about great performance improvement even in the 0% and 20% CACC cases. Notably, the algorithm performed well in the 0% CACC case in which the SPaT computation relies completely on the vehicle count and speed data obtained from fixed traffic sensors. With such limited datasets, the algorithm could still generate green time distributions that substantially improved speed and mpg and demonstrated the robustness of the proposed algorithm.

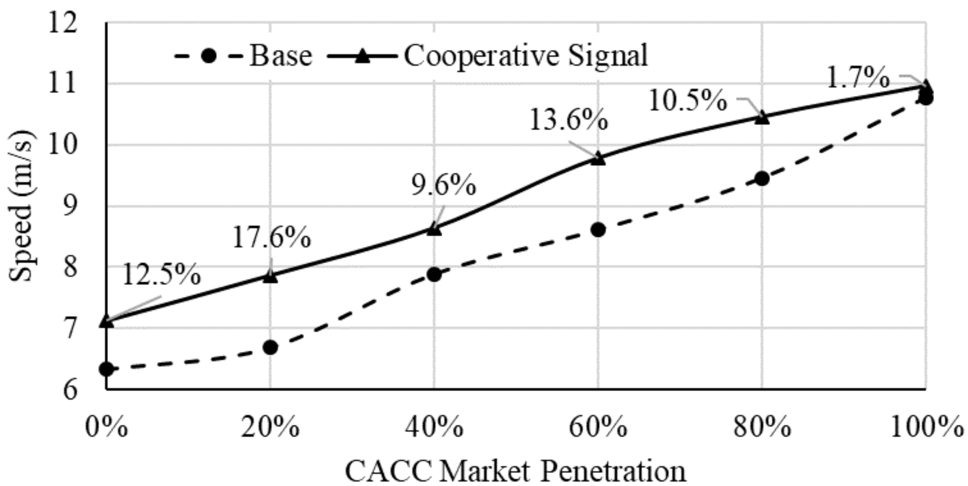


Figure 3-102. Average vehicle speed at an urban signalized intersection under various CACC market penetrations with and without cooperative signal controller.

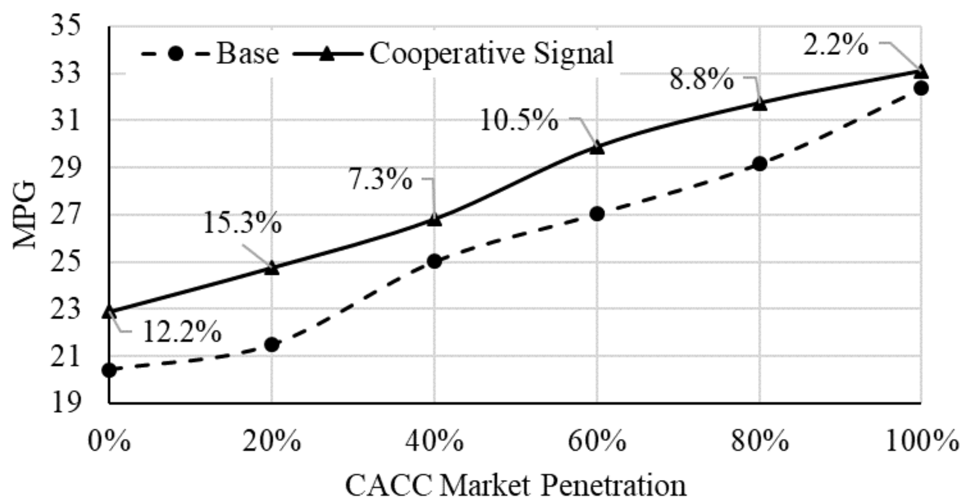


Figure 3-103. Average vehicle fuel economy (MPG) at an urban signalized intersection under various CACC market penetrations with and without cooperative signal controller.

To simulate mixed traffic with CAVs at signalized intersections, this work also considered incorporating trajectory planning for CAVs with active signal control.[160]

An intersection cooperative traffic signal control, as studied for the urban intersections mentioned above, is an aggregated control approach in the sense that it tells the vehicles of the corresponding phase and movement whether they should proceed or should not proceed, but it does not provide the vehicles with optimal trajectory assignments. For CACC-capable vehicle operation at the intersection, the central controller could provide a reference trajectory for each vehicle. The CAV Pillar researchers implemented this more detailed control in an attempt to better regulate individual vehicles and therefore the overall traffic.

Upon implementing the combined cooperative signal control algorithm with a vehicle trajectory planning strategy that minimizes the subject vehicle's fuel consumption, the added energy saving attributable to the implementation of the trajectory planning is not significant. Table 3-13 shows the average vehicle mpg when the CACC market penetration is 100%, and the traffic demand is 10% and 100% of the intersection capacity (measured in the manual driver case). Vehicle fuel efficiency shows only a minor increase when the demand is 10% of the intersection capacity, and the overall fuel economy becomes even worse when the demand is 100% of capacity. This means that when the intersection traffic is close to saturated, even the combined strategy with coordinated signal control and trajectory planning could be less effective in overall traffic optimization for energy saving than the cooperative signal only case, which means the trajectory planning algorithm can be improved.

In the 100% of capacity case, the trajectory planning algorithm asks the subject vehicle to start decelerating earlier than it does in the baseline case. At the signal initiated by the leader, the algorithm also causes the following vehicles to join the now-accumulating queue. Because of the early start of the queue accumulation, more vehicles upstream from the subject vehicle will be affected by the queue. Many of the queued vehicles would have passed the intersection without slowing down if the trajectory planning were not implemented. In this case, the benefit of the trajectory planning for individual subject vehicles is largely offset by the energy loss of the extra queued vehicles. Such an energy loss trend becomes greater as the traffic demand increases. This analysis indicates that the trajectory planning algorithm should be improved such that it optimizes both the fuel consumption of the subject vehicle and the overall traffic flow.

Table 3-13. Average vehicle MPG under traffic inputs of 10% and 100% intersection capacity (100% CACC).

	10% Capacity			100% capacity		
	Cooperative Signal Only	Cooperative Signal Plus Trajectory Planning	Δ	Cooperative Signal Only	Cooperative Signal Plus Trajectory Planning	Δ
Overall	31.4	31.5	0.1%	29.4	29.2	-0.8%
NB	32.1	32.1	0.0%	30.1	29.8	-0.9%
SB	32.0	32.1	0.3%	29.8	29.5	-0.8%
WB	20.6	20.5	-0.6%	19.9	19.7	-1.3%
EB	18.5	18.3	-1.3%	20.8	20.7	-0.4%

Traffic microsimulations have been developed and applied to show the significant potential for energy savings through use of cooperative vehicle following automation (CACC) — and the potential for adverse effects when the automation is non-cooperative. These tools were used for specific scenarios in specific freeway corridors, but now that they have been developed and refined, they are available for use to represent a much wider range of CAV scenarios, including higher levels of automation. When high percentages of the passenger cars on a freeway use cooperative vehicle following, they can dramatically reduce congestion and increase the effective throughput of the highway, yielding significant energy savings.

The performance of a cooperative signal control algorithm has been tested against an actuated signal control with a simulated four-way intersection. The test results show that the algorithm can improve both the average intersection speed and the average vehicle mpg. The most significant impact was observed in the lower CACC market penetration cases. In those cases, the algorithm can substantially improve traffic mobility and vehicle fuel economy by reducing or eliminating the need to wait for multiple cycles before passing the intersection. In the medium and high CACC market penetration cases (Figure 3-103), the algorithm performs best when the traffic demand is close to the intersection capacity measured under the actuated signal control. A preliminary analysis was performed that quantifies the intersection performance when the proposed signal control algorithm is combined with a vehicle trajectory planning algorithm. However, the results show that the trajectory planning algorithm cannot create extra benefits when implemented with the signal algorithm. This finding suggests that there is a need to develop more advanced trajectory planning (or eco-approaching) algorithms to enhance the proposed cooperative signal control algorithm.

3.4.2.3 CAV-Enabled Optimal Coordination Strategies and Impacts for Highlighted Traffic Scenarios

- With partial penetration of CAVs and a heterogeneous fleet (different vehicle classes from light-duty to heavy duty), the optimal coordination framework developed by the CAVs Pillar provided fuel savings of 3% to 30% for a highlighted freeway merging scenario under moderate to heavy traffic.
- With full penetration of CAVs, the optimal coordination framework developed by the CAVs Pillar enabled the vehicles crossing a roundabout to reduce fuel use ~27% and travel time between 3% and 49%, depending on the traffic conditions.
- In a simplified highway corridor with full penetration of CAVs, the developed optimal coordination mitigated traffic jam propagation, leading to travel time savings of up to 40% and improvements in fuel economy of up to 55% over the non-coordinated scenario.
- At lower CAV penetration levels, in a longer, real-world corridor, the developed coordination framework still achieved a significant overall corridor fuel consumption reduction. For example, at 20% CAV penetration, a fuel consumption reduction of 4% was achieved.

The goals of energy-efficient mobility systems are to alleviate congestion, reduce energy use and emissions, and improve safety. At the vehicle and corridor level, core technologies include vehicle connectivity, vehicle automation, and the notion of a cooperative transportation infrastructure enabled by these advanced mobility technologies. Intersections, merging roadways, speed reduction zones (SRZs), and the drivers' responses to various disturbances are currently the primary sources of bottlenecks that contribute to traffic congestion and stop-and-go driving, with significant implications in both fuel consumption and traffic stability. In 2017, congestion caused people in urban areas in the United States to spend 8.8 billion hours more on the road and purchase an extra 3.3 billion gallons of fuel, resulting in a total cost estimated at $166 billion.[161]

CAVs provide a promising opportunity for enabling users to better monitor transportation network conditions and improve traffic flow. CAVs can be controlled at different transportation segments, such as intersections, merging roadways, roundabouts, and SRZs, and can assist drivers in making better operating decisions to reduce pollution, fuel consumption, and travel delays as well as improve safety.

Most of the current research related to the control and coordination of CAVs has focused on safety and travel time. Several studies have attempted to quantify the energy implications of proposed control and coordination strategies with the assumption of full penetration of CAVs. However, the implications of partial penetration rates of CAVs on energy and travel time have been an under-explored aspect within the research community. This work explores the impacts of an optimal coordination framework for CAVs[162] in the presence and absence of interactions with human-driven vehicles (i.e., assuming partial and full penetration rates of optimally coordinated CAVs) under different traffic conditions. The main focus areas of this work are (1) the development and expansion of a simulation framework to capture the interaction of CAVs with human-driven vehicles under different traffic volumes for a range of traffic scenarios, and (2) the analysis of the impact that different penetration rates of CAVs have on fuel consumption, travel time, and traffic flow when the optimal coordination framework is applied.

3.4.2.3.1 Speed Harmonization through Optimal Coordination-Full Penetration of CAVs

- The proposed optimal coordination algorithm significantly reduced fuel consumption for each vehicle in a speed harmonization (SPD-HARM) scenario by 19%–22% over the baseline scenario and showed improved performance compared with other SPD-HARM strategies proposed in the research literature.

To evaluate the effectiveness of the CAVs Pillar developed optimization framework for SPD-HARM, a single-lane freeway corridor was implemented in the Vissim application programming interface as shown in Figure 3-104 and Figure 3-105. The corridor was 2,000 m long, including an SRZ 300 m long located downstream. Because capacity dropped at the entrance of the SRZ, stop-and-go congestion was meant to be generated under the baseline scenario even without feeding additional volumes through ramps. The speed limit inside the SRZ was set to be 15.6 m/s. Upstream of the SRZ, a 300 m control zone (CZ) was defined. Neither the speed limit at the SRZ nor the length of the CZ affected the analytical solution for system optimality.[163] However, varying the length of the CZ or the speed limits might yield different quantitative results for fuel consumption, travel time, and throughput.

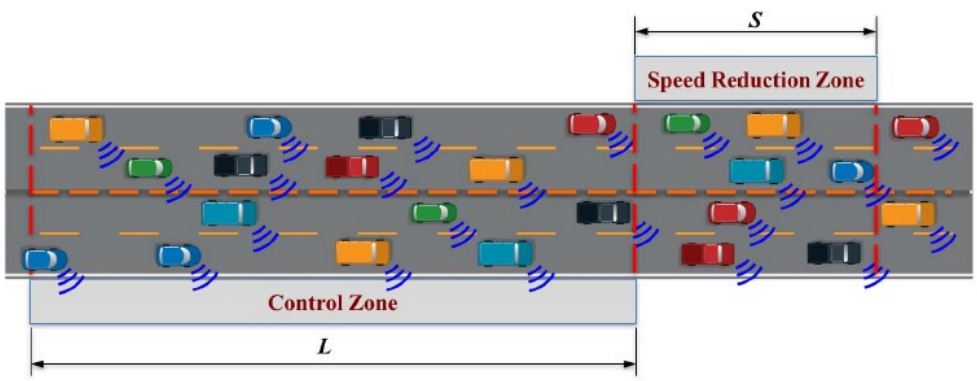


Figure 3-104. Automated vehicles within a control zone approaching a speed reduction zone.

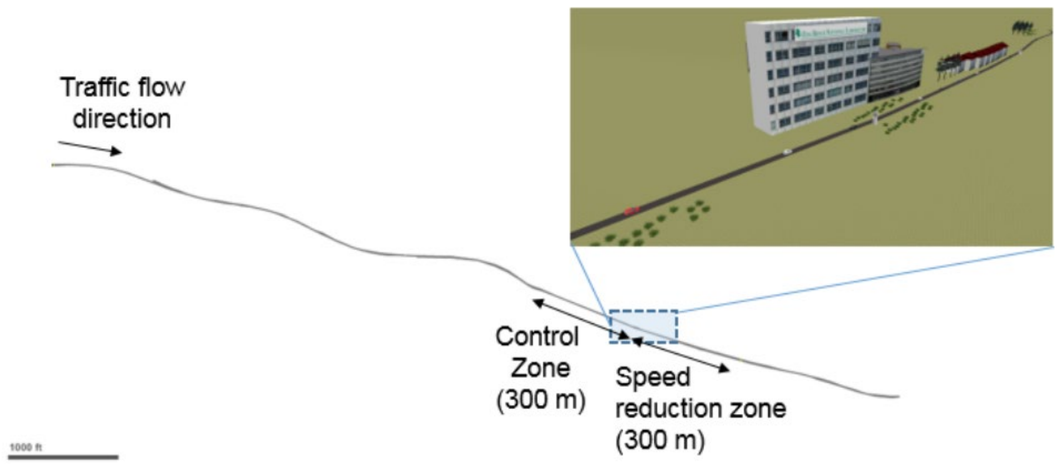


Figure 3-105. Traffic network developed in VIssim for the speed harmonization case.

The following traffic flow scenarios were considered: (1) 1,620 veh/h, (2) 1,800 veh/h, and (2) 1,980 veh/h, with a total simulation time of 1,000 s, and the following three approaches were compared: (1) a baseline scenario with human drivers (Wiedemann car-following model), (2) a state-of-the-art variable speed limit (VSL) algorithm called speed controlling algorithm using shock wave theory (SPECIALIST[164]), and (3) the vehicular-based SPD-HARM algorithm proposed by the U.S. Department of Transportation.[165] The results for fuel consumption, travel time, and throughput for each approach and simulated traffic flow are shown in Figure 3-106. The proposed control algorithm significantly reduced the fuel consumption of each vehicle over the combined CZ (300 m) and SRZ (300 m) by 19%–22% over the baseline scenario, by 12%–17% over the VSL algorithm, and by 18%–34% over the vehicular-based SPD-HARM algorithm for the three traffic volume cases considered. When the vehicular-based SPD-HARM was used, fuel consumption was not statistically different from that of the baseline scenario for Scenarios 1 and 2. For Scenario 3, fuel consumption increased by 18% over the baseline scenario.

With the optimal control, travel time and throughput were improved over the baseline scenario, VSL, and vehicular-based SPD-HARM algorithm for all traffic volumes. In particular, travel time was improved by 26%–30% over the baseline scenario, by 3%–19% over the VSL algorithm, and by 31%–39% over the vehicular-based SPD-HARM algorithm for the three traffic volumes. Both the VSL and the proposed control algorithm reduced the travel time and improved the vehicle throughput under all three traffic volumes. The proposed control algorithm also reduced travel time by 19% and throughput by 3% compared with the VSL under Scenario 3.

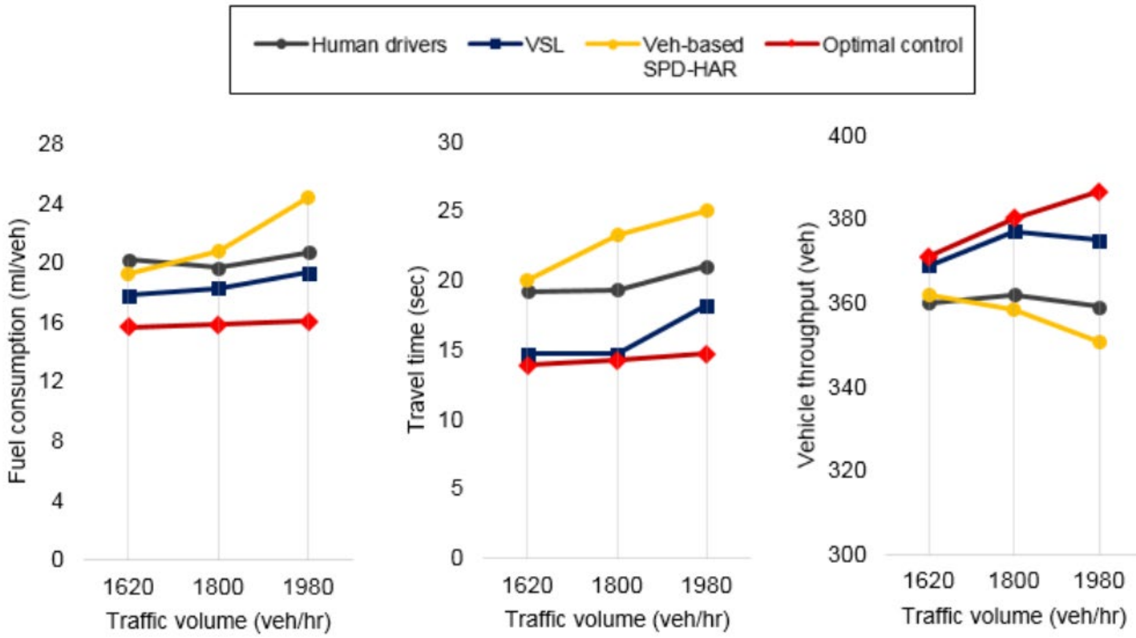


Figure 3-106. Comparisons of the baseline scenario (human-driven vehicles), VSL, and optimal control algorithm.

3.4.2.3.2 Vehicle Merging at a Highway On-Ramp

- At full penetration of CAVs and with a homogeneous vehicle fleet (i.e., light-duty vehicles (LDVs)), the developed optimal coordination framework reduced fuel consumption more than 40% while also reducing travel time.
- With partial penetration of CAVs and a heterogeneous fleet (i.e., different vehicle classes from light- to heavy-duty), the optimal coordination framework developed by the CAVs Pillar provided fuel savings of 3%–30% in moderate to heavy traffic.
- With low traffic and lower CAV penetration rates, a high level of uncertainty existed regarding whether or not the benefits of optimal coordination and fuel consumption could increase. At higher market penetration rates (MPRs) of CAVS with low traffic, the fuel savings varied from 2% to ~12%.

3.4.2.3.2.1 On-Ramp Merging — Full Market Penetration of CAVs

A single on-ramp (Figure 3-107) scenario was simulated in MATLAB as a first step in assessing the impact of optimal coordination of CAVs in different traffic conditions[166] considering (a) a baseline case with 0% CAV penetration, and (b) an optimal case with 100% CAV penetration. In the baseline case, the drivers' behavior was represented by the Gipps car-following model.[167] In the optimal case, CAVs behaved according to the developed optimization framework for merging coordination.[168]

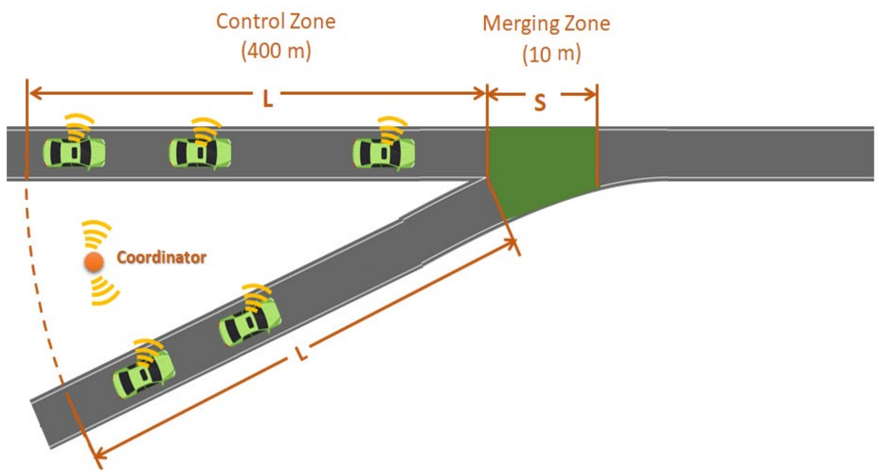


Figure 3-107. Simulated merging on-ramp.

The two cases were simulated considering different traffic demands. For each simulation, traffic data (travel time, traffic volume, average speed, and queue) were aggregated at 30 s intervals and used to capture the macroscopic traffic flow and density for both scenarios. The total fuel consumption and total travel time for all the vehicles crossing the control and merging zone (total length of 430 m) were used as measures of effectiveness. To quantify the total fuel consumption, a polynomial metamodel was applied that calculates vehicle fuel consumption as a function of speed and acceleration.[169]

The left plot in Figure 3-108 shows that the optimal merging coordination framework enabled CAVs to significantly reduce fuel consumption under all the simulated traffic demands. The total system-level fuel savings compared with the 0% CAV scenario varied widely depending on the traffic conditions, but overall, under lower traffic demands, the savings were about 35%–40%. The higher fuel savings were found in average traffic, given that the vehicles still had some freedom to accelerate/decelerate in an optimal way, as opposed to the case of heavy traffic, in which the vehicles were more constrained in their responses. Therefore, in heavier traffic, the vehicles experienced smaller headways, and the idling condition (i.e., the vehicle engine was running and consuming fuel while the vehicle was stopped) started dominating, thus reducing the potential to save fuel. Still, the average fuel savings in heavier traffic were about 20%.

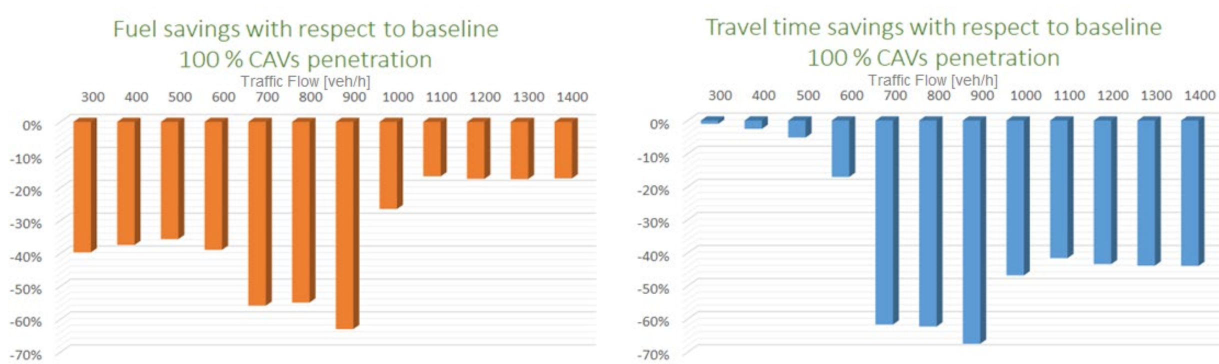


Figure 3-108. System-level fuel consumption (left) and travel time (right) savings for different traffic demands (traffic flow volume was the same on the main and ramp roads).

However, the total travel time (Figure 3-108 right) remained very close for the 0% and 100% CAV cases in low traffic conditions, but varied widely in the 100% penetration case for medium and high traffic compared with the baseline case.

3.4.2.3.2.2 On-Ramp Merging — Partial Market Penetration of CAVs

The overall objective of the optimal lane merging coordination was to enable smoother driving patterns by controlling the merging sequence and optimizing the vehicles' speed profiles. The fuel and emissions implications of such optimal coordination for an on-ramp (Figure 3-109) modeled in Vissim were assessed. The CZ was 400 m long and the main road was 1 km long. For the human-driven vehicles, the drivers' behavior was represented by the Wiedemman car-following model.[170] The estimates for fuel consumption and emissions were obtained using the vehicle models and fleet distribution used in the SMART workflow baseline Base0, representing the current day (refer to the SMART Mobility Modeling Workflow Capstone Report Section 3.2.2 - Common Scenarios and Assumptions-Vehicle Assumptions and Fleet Distribution).

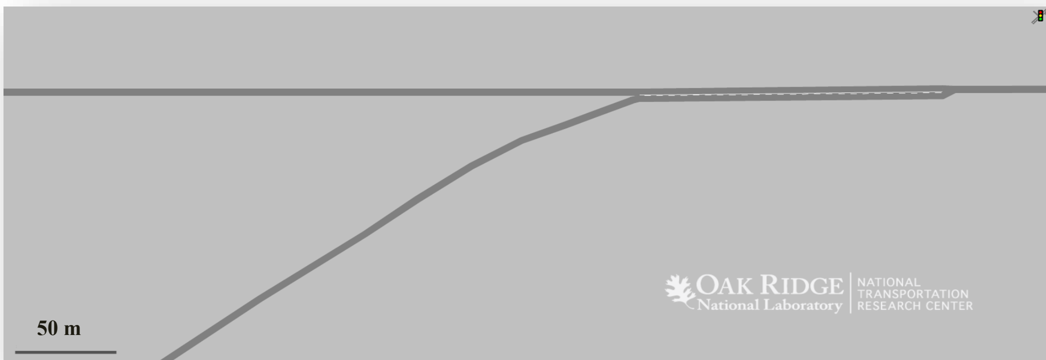


Figure 3-109. Merging on-ramp used for assessment of fuel, energy and emissions implications.

Three traffic volumes were simulated (1,800 veh/h, 2,000 veh/h, and 2,200 veh/h) and a 60% to 40% split between the main and ramp roads was assumed. To account for different CAV market penetration rates, the penetration scenarios described in Table 3-14 were used.

Table 3-14. Simulated CAVs market penetration scenarios

	CAV Market Penetration Scenarios											
	Baseline	2	3	4	5	6	7	8	9	10	11	12
% Light-Duty CAVs	0	0	5	10	20	40	50	60	80	90	95	100
% Heavy Duty CAVs	0	100	100	100	100	100	100	100	100	100	100	100

The results shown in Figure 3-110 show that the benefits were sensitive to traffic demand. The higher benefits in terms of average fuel consumption (5% to ~30%), occurred in scenarios with moderate congestion (e.g., 2,000 veh/h) because the vehicles still had some freedom to accelerate/decelerate in an optimal way. At lower traffic demands (e.g., 1,800 veh/h), the reduced traffic on the main road allowed more human-driven cars to merge without conflicts in the baseline scenario, avoiding significant acceleration/deceleration changes. This success resulted in smoother travel patterns than in moderate traffic and thus reduced opportunities for improvement. However, the benefits at lower traffic volume in average fuel savings and fuel economy at full penetration exceeded 10%. In heavy traffic, the vehicles were more constrained in their responses because of the smaller headways and because the idling condition started dominating, reducing the potential to save fuel and improve the average fuel economy. Still, the average fuel savings in heavier traffic varied between 2% and 17%.

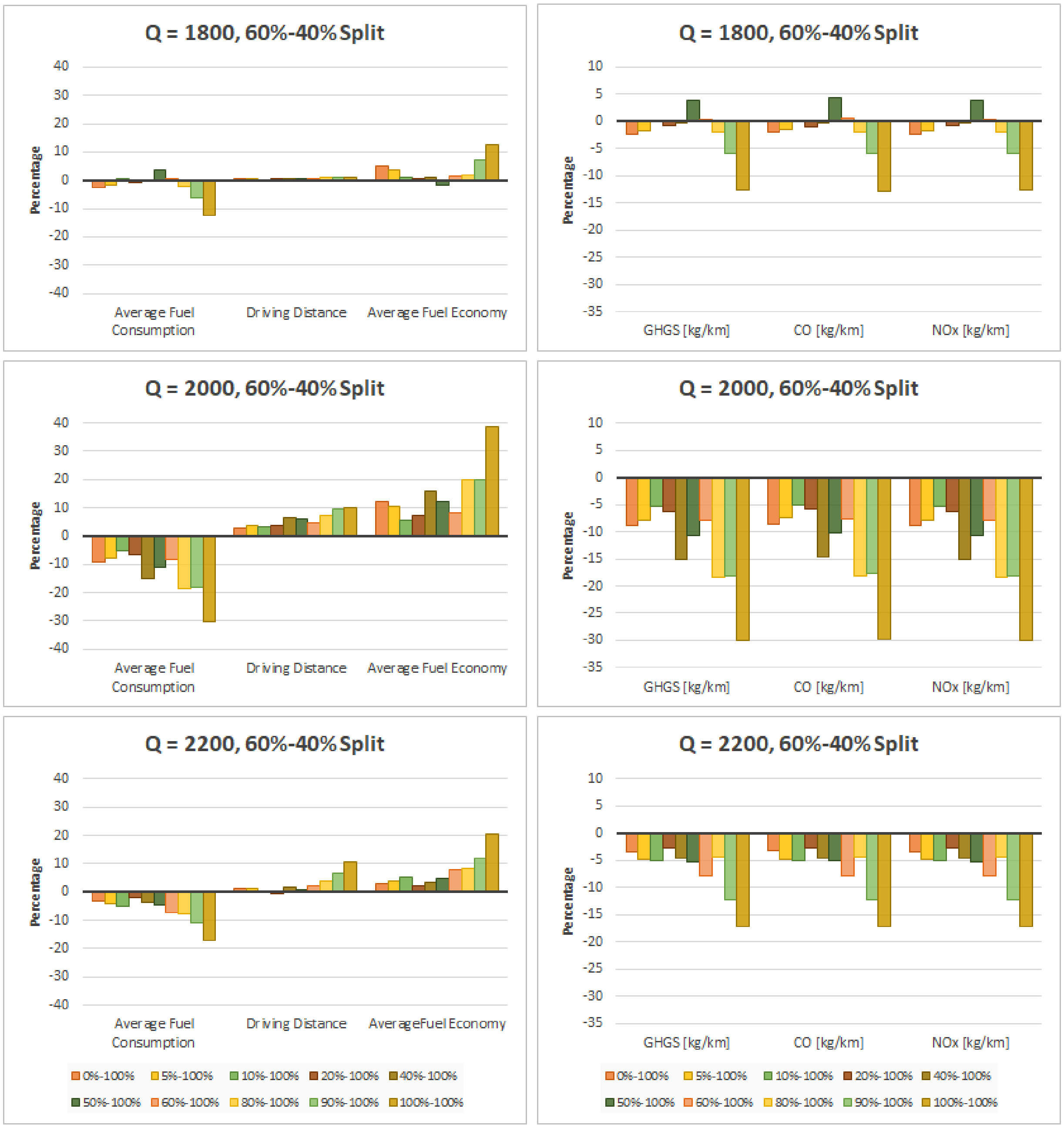


Figure 3-110. Average fuel consumption, driving distance, fuel economy, and emissions changes compared to baseline over the 1 km corridor for three traffic demands (1,800 veh/h, 2,000 veh/h, and 2,200 veh/h; 60%–40% split between the main and ramp roads) with various CAV market penetration rates (numbers in the legend identify the percentages of light- and heavy-duty CAVs).

For higher penetration rates (over 60%), the coordinated operation of an increasing number of CAVs on the road allowed an almost proportional increase in fuel consumption savings and average fuel economy. In addition, the total distance all the vehicles in aggregate could travel during a set simulation period increased with the penetration rate when the traffic demand was moderate to high and remained almost constant for the lower traffic demand. Since at moderate to high traffic demand, coordinated operation allowed vehicles to travel faster than in the baseline, the vehicles traveled farther in the same simulation time and more vehicles were able to enter the simulation, increasing the total traveled distance.

At lower penetration rates, for all the simulated traffic demands, increased uncertainty and performance variability exist regarding the fuel consumption savings and average fuel economy. This result suggests that low market penetration scenarios will likely also see higher variability in performance in the real world. As the number of CAVs increases, more vehicles will be trying to communicate and merge in a coordinated way. However, they will still be constrained by the “random” behavior of human drivers and the lack of accurate information about their decisions and intentions. In these mixed partial penetration scenarios, CAVs need to rely on their own estimations (through sensors) to ensure collision-free trajectories. Thus, CAV efficiency will be adversely affected by the unsmooth driving of the human-driven vehicles when attempting to merge and will be required to perform harder acceleration/deceleration and stopping maneuvers to ensure safety, which will affect the downstream traffic. These erratic maneuvers result in variable fuel consumption trends.

The authors applied the control in a receding horizon fashion, which implies that the optimal control was updated at every sample time of the simulation to account for the behavior of the human-driven vehicles. With this approach, a CAV on the main road could start following the optimal control, but a human driver on the on-ramp, initially positioned to merge behind the CAV, could decide to accelerate to merge in front. In a situation like this, as soon as the CAV becomes aware of the human-driven vehicle, it will have to update its optimal control law (i.e., slow down to ensure a safety gap behind the new leader). This required deceleration comes at the price of additional acceleration needed later to arrive at the merging zone at the desired speed. Required to ensure safety, these changes in acceleration will affect the upstream traffic, increasing the fuel consumption. Furthermore, as the MPR increases, more vehicles are following the optimal control, which changes the behavior of the human drivers, thus increasing the uncertainty.

The plots in Figure 3-111 illustrate this type of situation in the simulation through three consecutive vehicles. Scenario 1 represents 0%:0% (LDV:HDV) MPR or baseline, Scenario 6 represents 40%:100% MPR, Scenario 8 represents 60%:100% MPR, and Scenario 12 represents 100%:100% MPR. Red and blue plots illustrate the behavior of CAVs and non-CAVs (human drivers), respectively, and the green shaded area indicates the length of the CZ for CAVs. The speed traces in the baseline scenario illustrate how the human (VehID 25) will brake suddenly when approaching the merge area at 800 m to accelerate again later to reach the desired speed. This sudden braking event is amplified in the two followers (VehID 26 and 27), which have to reduce their speed to close to 0 and accelerate again until reaching the desired speed.

In Scenario 6 (where 40% of the LDVs were CAVs), vehicle 25 was a CAV and anticipated a vehicle merging in front of it, thus starting the braking phase at the beginning of the CZ. Although this anticipation already smoothed out the speed and acceleration profiles, a readjustment of the optimal speed profile was needed before the 700 m marker because of unanticipated behavior of the merging vehicle. In Scenario 8 (when 60% of the LDVs were CAVs), the readjustment of the optimal profile happened after the 700 m marker and required another braking event from vehicle 25, making the speed and acceleration profiles more erratic than in Scenario 6. The erratic speed of vehicle 25 once again shaped the response of the human followers. In contrast, although a small readjustment of the optimal control was observed in Scenario 12, the speed and acceleration profiles were significantly smoother than in the previous case. Scenario 12 still followed a receding horizon approach to account for potential unexpected events on the road (not likely to happen in simulation) and delays in the vehicle response, which can be more critical for HDVs.

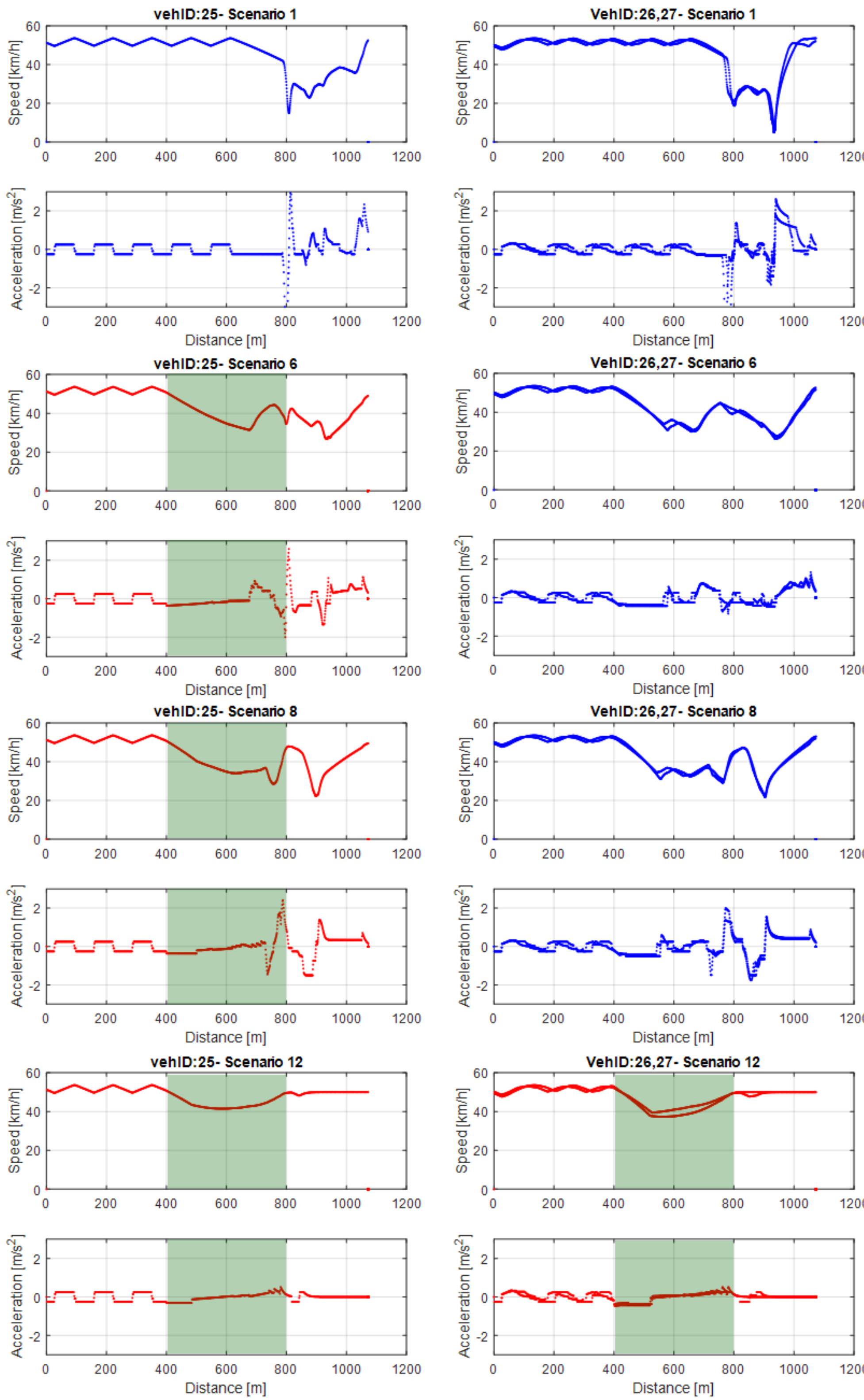


Figure 3-111. Speed and acceleration profiles for three consecutive vehicles in scenarios 1, 6, 8 and 12 described in Table 3-14.

Future work could investigate the benefits of integrating human behavior predictions and how to enhance interactions between human drivers and CAVs to reduce the uncertainty found with low MPRs. Furthermore, additional work could be done to better understand the implications of optimal merge coordination on vehicles with electrified powertrains. Finally, scenarios considering short-term and long-term vehicle fleets distributions could be analyzed to understand the potential benefits of coordination in the future.

3.4.2.3.3 Roundabout Coordination — Full Penetration of CAVs

- With full penetration of CAVs, the optimal coordination framework developed by the CAVs Pillar enabled the vehicles crossing a roundabout to save up to ~27% in fuel and between 3% and 49% in travel time, depending on the traffic conditions.[171]

This work simulated a simple roundabout network of 310 m (Figure 3-112). To evaluate the impacts of optimal coordination of CAVs for different traffic conditions, two scenarios were created: (a) a network with 0% CAV penetration (baseline) and (b) a network with 100% CAV penetration. Additionally, to test the control's effectiveness under different traffic conditions, a set of east and west entry volumes varying from 300 veh/h to 1,000 veh/h were investigated. The CAV Pillar-designed optimal coordination algorithm in was implemented using Vissim[172] to represent the CAV operations, and the Wiedemann car-following model[173] was selected to represent the drivers' behavior in the baseline case. Every 60 s, the aggregated data, including travel time, volume, and queue, were recorded for network performance evaluation.

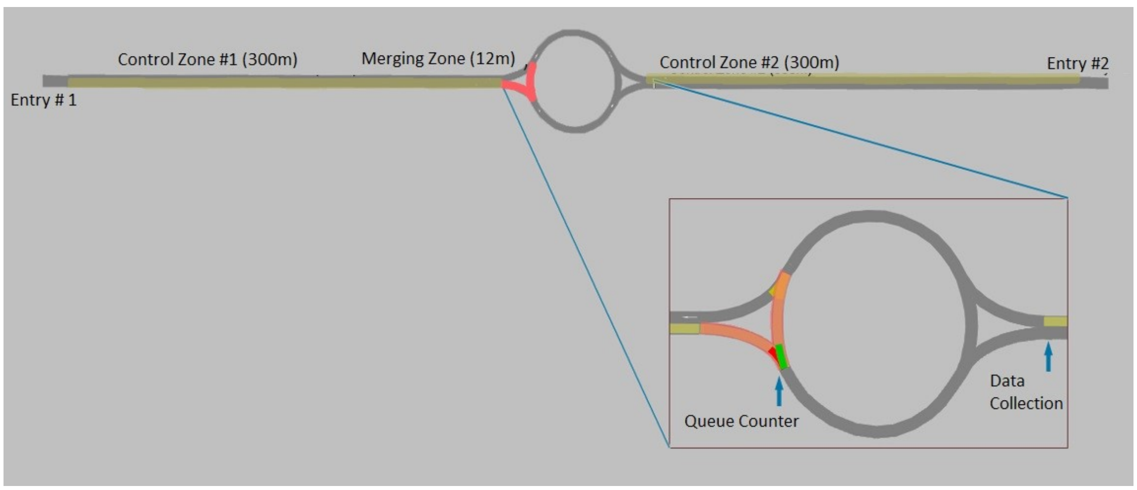


Figure 3-112. Simulated roundabout.

In low traffic, the headways between westbound traffic were generally large enough that few eastbound vehicles needed to stop before entering the roundabout. In the baseline scenario, as entry volume increased, eastbound traffic experienced more difficulty in finding proper gaps into which to merge, resulting in a queue built up until the end of the simulation. With the proposed control algorithm, network throughput was improved, and the eastbound vehicles could merge into the roundabout without stops, even with a high circulating flow. As shown in Figure 3-113, the queue for eastbound traffic was eliminated with the proposed approach. Therefore, the total number of vehicles exiting the roundabout increased, leading to improved roundabout capacity (e.g., 25% improvement with 1,000 veh/h per lane entry volume).

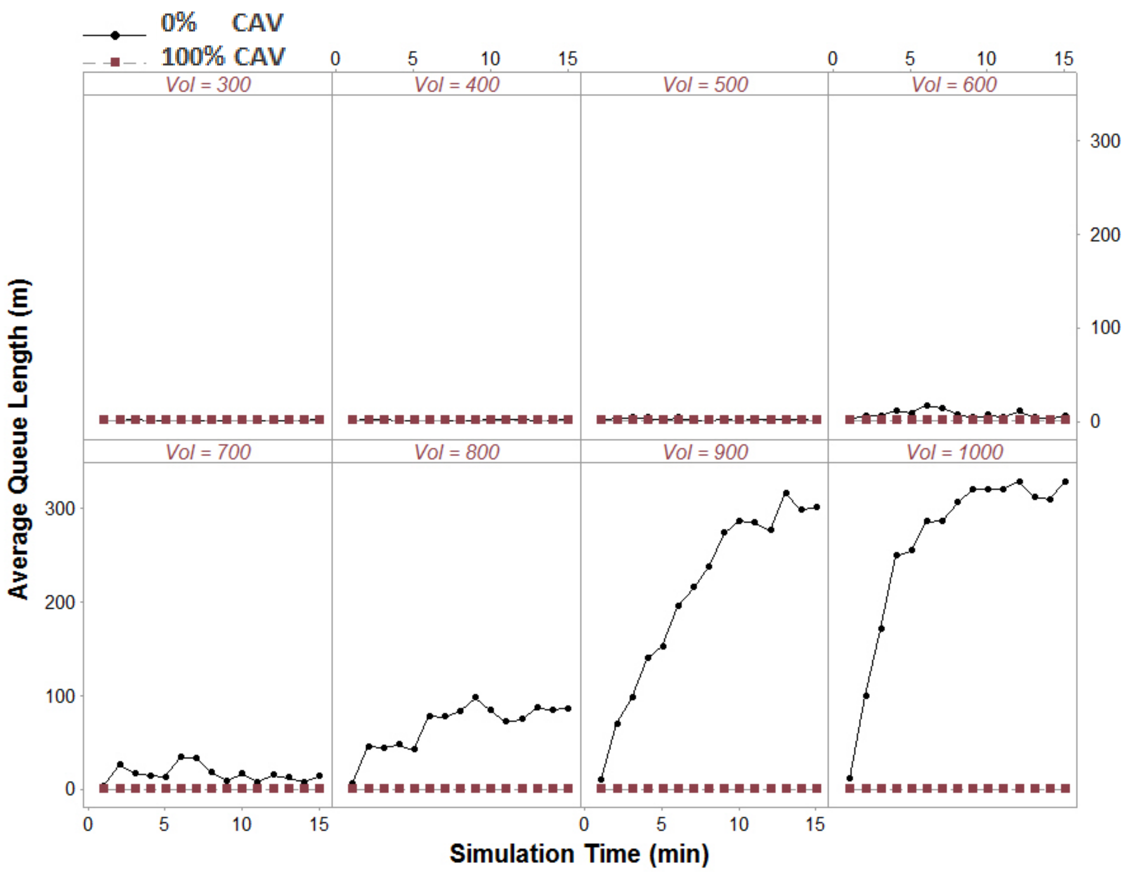


Figure 3-113. Average queue length for eastbound traffic, volume given in veh/h.

Through vehicle coordination, the large variation in traffic conditions was minimized and the overall network travel time (Figure 3-114) improved significantly. Therefore, under different traffic conditions, travel time savings of 3%–49% was observed for the entire network. Furthermore, by eliminating stop-and-go driving for eastbound traffic, transient engine operation was minimized, leading to direct fuel consumption savings as shown in Figure 3-114.

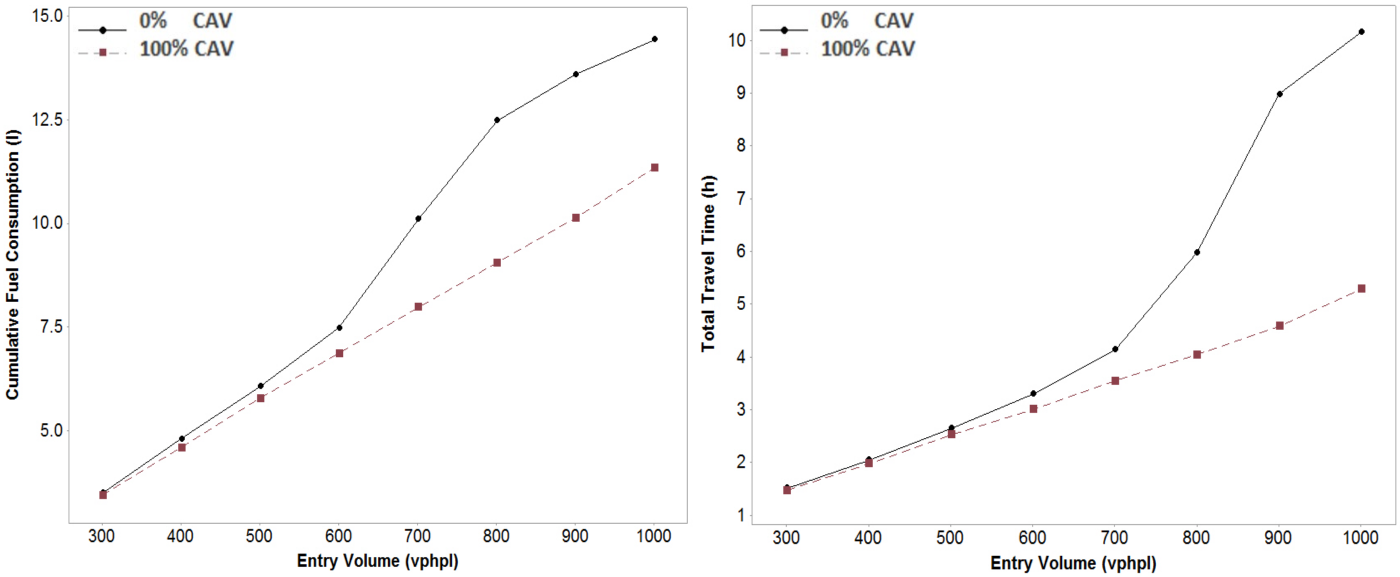


Figure 3-114. Total fuel consumption and total travel time vs. entry volume.

3.4.2.3.4 Optimal Intersection Coordination — Full Penetration of CAVs

- With full penetration of CAVs, because vehicles no longer need to stop, and acceleration is optimized in the CZ, the optimal coordination framework applied to an intersection achieved a fuel consumption improvement of 47%, and the travel time was improved by 31%.

The optimal coordination framework was adapted to coordinate the vehicles crossing an intersection, as illustrated in Figure 3-115. To evaluate the effectiveness of the coordination algorithm in this case, two actual intersections in tandem located in Boston were implemented in Vissim. The authors modeled a case in which 434 vehicles were coordinated to cross the intersections. The proposed solution was compared with a baseline scenario in which the intersections had traffic lights with fixed switching times. To quantify the impact of the vehicle coordination on fuel consumption, the authors used the same polynomial metamodel.[174]

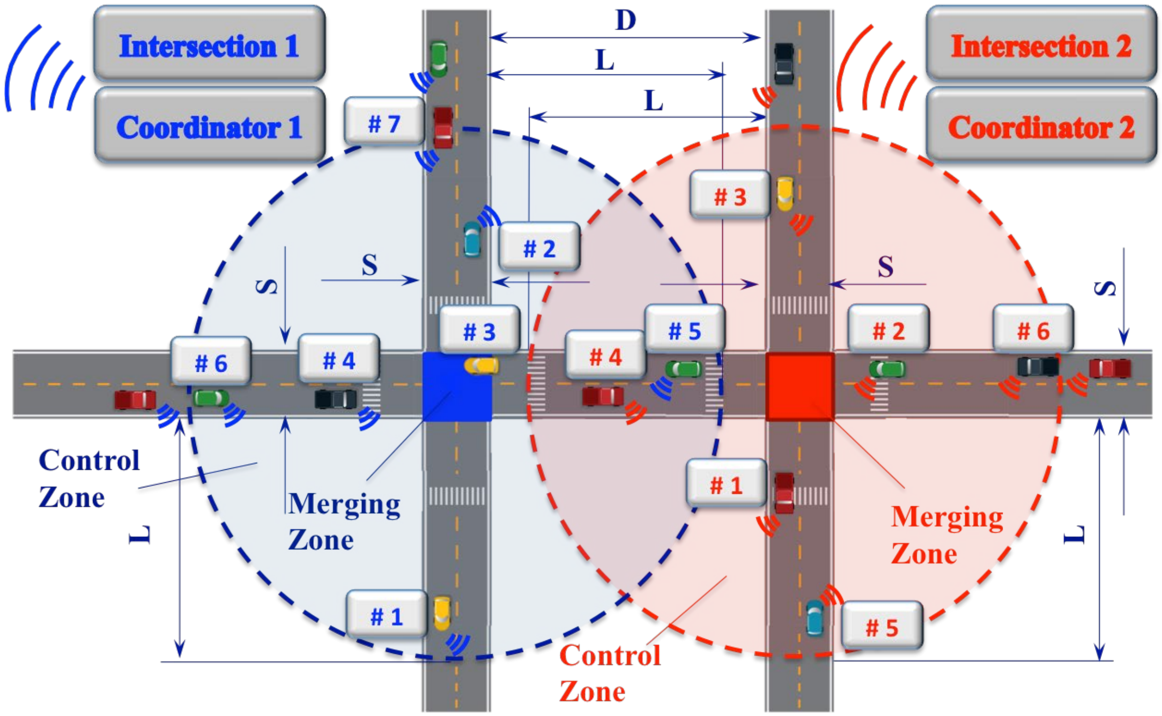


Figure 3-115. Two intersections in tandem used in the work with connected and automated vehicles.

Only one lane in each direction was modeled. The authors set the CZ length to 245 m (when possible) and the merge zone to 35 m for both intersections. Since the shapes of the actual intersections were not regular, the distance between them was not the same for different directions: The distance in the westbound lane (traffic flow from the east) was 160 m, and the distance in the eastbound lane (traffic flow from the west) was 145 m. In this work, the coupling of the two intersections was not considered when selecting optimization parameters. The vehicle arrival rate was assumed to be given by a Poisson process with a traffic flow of 450 veh/h for each lane. A comparison with the baseline scenario using traffic lights is shown in Figure 3-116. The fuel consumption improvement was 46.6%, and the travel time was improved by 30.9%. The fuel consumption improvement was due to the following: (1) the vehicles did not come to a full stop, thereby conserving momentum, and (2) each vehicle traveled with the minimum acceleration/deceleration in the CZ, so transient engine operation was minimized with direct benefits in fuel consumption.[175]

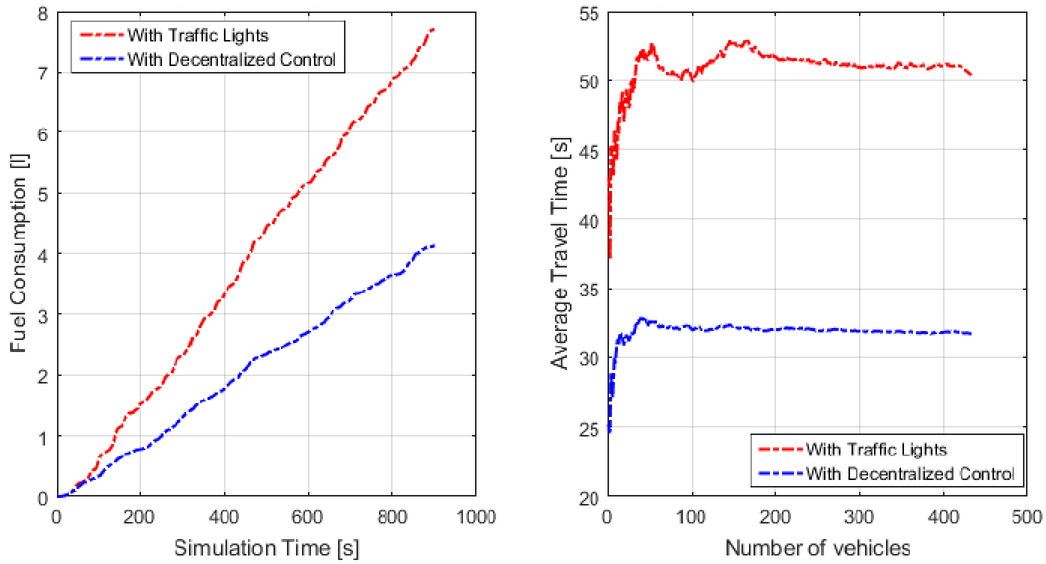


Figure 3-116. Fuel consumption and average travel time improvement for the 434 vehicles passing through the simulated intersections. East-west and west-east corridors were 440 m and 425 m long, respectively.

3.4.2.3.5 Urban Corridor Coordination — Full CAVs Penetration

- Through the developed optimal control algorithm, average fuel consumption savings of 35% to ~42% per vehicle was achieved for the urban corridor in moderate to heavy traffic.
- With the objective of minimizing energy consumption and keeping safer gaps between the vehicles, the average corridor travel time slightly increased (~3%) in light traffic, given that most human-driven vehicles in the baseline case could find appropriate gaps to merge into mainline traffic flow without stops.

Using Vissim, the CAVs Pillar defined a study corridor in the University of Michigan's Mcity[176] that consisted of a highway on-ramp, an SRZ, a roundabout, and an intersection (Figure 3-117).

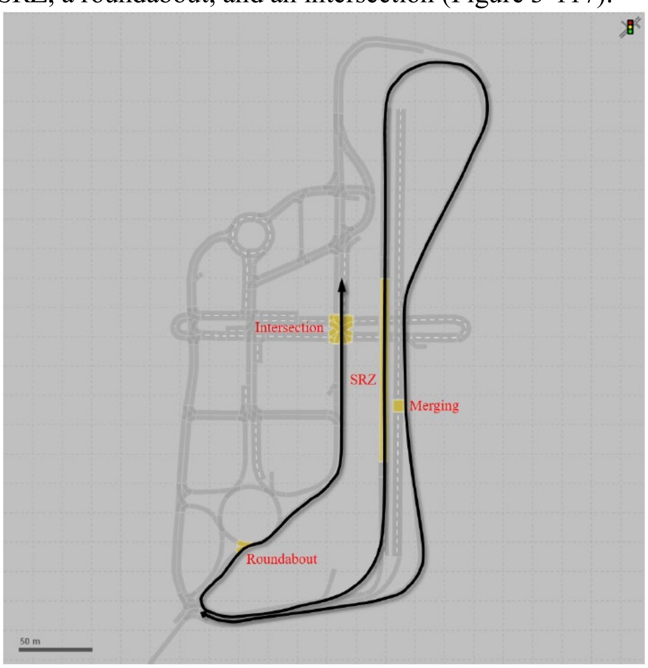


Figure 3-117. Simulated urban corridor.

Vehicles entered the network via the on-ramp, joined the traffic on the highway with a desired speed of 25 m/s (~55 mph), and then entered the SRZ, where the speed limit drops to 11 m/s. Exiting from the highway segment, the vehicles traveled through the roundabout, where a desired speed of 13 m/s was in effect until the vehicles crossed the intersection to reach the end of the path (corridor length 1.26 km). To evaluate the network performance with the proposed control algorithm, two cases with different traffic demand levels were analyzed. Case 1 represents the baseline scenario in which all vehicles in the network were non-connected and non-automated, and a traffic light controlled access to the intersection. In this case, the Wiedemann car-following model built into Vissim was applied. A time headway of 1.2 s was adopted given the minimum allowable following distance. Case 2 represents the optimal case (100% market penetration of CAVs), where all the vehicles followed the proposed optimal control algorithm. The control framework was applied in this case to recommend optimal acceleration/deceleration for each CAV in the network. The same time headway as in case 1 was applied in the optimal control model. Table 3-15 summarizes the traffic scenarios created (and evaluated) for the baseline and optimal cases.

Table 3-15. Summary of traffic scenarios.

Scenario	Ramp (veh/h)	Highway (veh/h)	Urban (veh/h)
1	200	600	300
2	300	1000	500
3	400	1400	600

The speed profile plots for the baseline and optimal control cases for all the vehicles in the corridor are shown in Figure 3-118. The locations of the on-ramp, SRZ start and end positions, roundabout entry point, and intersection are also marked in the figure. For baseline cases, where no control was in effect, the vehicles had to yield to mainline traffic and wait for a green light in the intersection. When mainline traffic flow was low, merging vehicles could often find gaps to merge into the mainline flow without stopping (e.g., baseline case in Scenario 01 in Figure 3-118). As the traffic demand increased, more vehicles had to stop before merging, and the queues backed up in the intersection, leading to a further delay in the baseline cases. In addition, under the high traffic demand condition, a large variation in baseline vehicle speed profiles existed, leading to unbalanced traffic flow and underused corridor capacity.

On the other hand, in the optimal control cases, traffic information for the entire corridor was shared with all vehicles, so the vehicles traveling along the corridor could drive more smoothly and avoid hard acceleration/deceleration for any merging or speed reduction events in the path. With an increased traffic demand, CAVs had to decelerate/accelerate harder before entering the conflict zones to create proper gaps for each other to successfully merge without stopping.

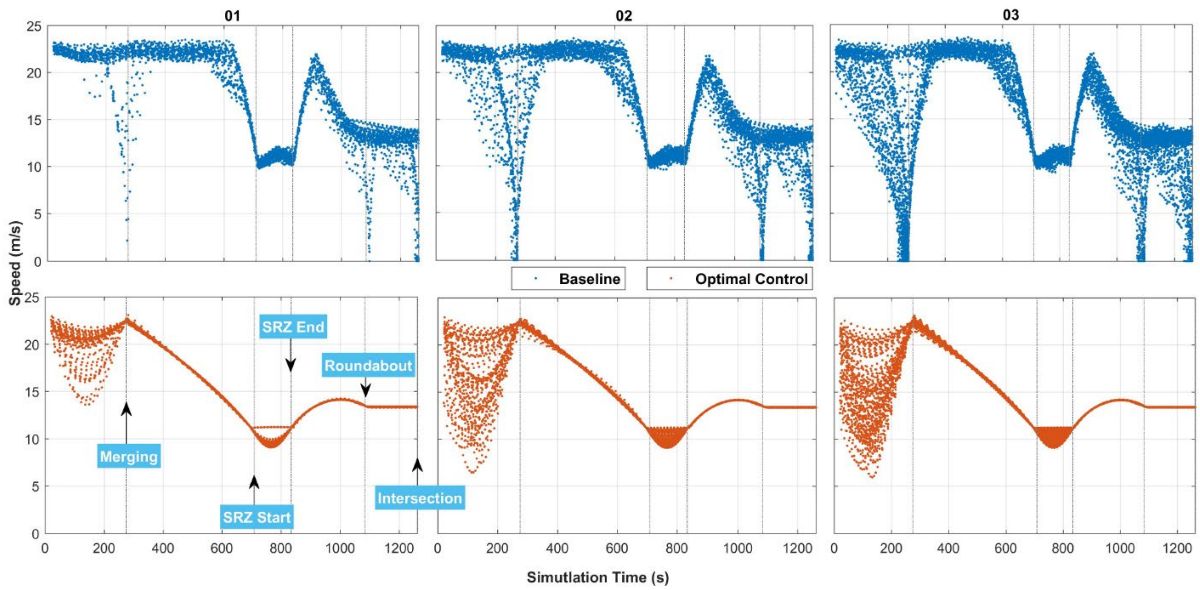


Figure 3-118. Speed profiles for the vehicles in the urban corridor under different scenarios.

Although CAVs were immediately preparing for following conflict zones, the human-driven vehicles travelled with higher speeds until they were aware of the downstream conflict zones. CAVs coordinated with each other to create gaps for merging and crossing the intersection, while human-driven vehicles had to stop for mainline vehicles and wait for a green light to cross the intersection. As the traffic demand increased, a large speed drop was unavoidable even in the optimal control cases. Nevertheless, through the optimal control algorithm, a 35% to ~42% savings in average fuel consumption per vehicle was achieved over the length of the corridor (1.26 km) during the simulation period (Figure 3-118). With the objective of minimizing energy consumption and keeping safer gaps between the vehicles, the average corridor travel time was slightly increased (~3%) in the light traffic conditions in which most human-driven vehicles in the baseline case could find gaps to merge into the mainline traffic flow without stops.

3.4.2.3.6 Simple Highway Corridor Coordination

- At full penetration of CAVs, for a simplified highway corridor, the developed optimal coordination mitigated traffic jam propagation, leading to travel time savings of up to 40% and improvements in fuel economy of up to 55% compared with the non-coordinated scenario.
- Introducing high penetrations of optimally coordinated light-duty CAVs (i.e., 60%–80%) smoothed major traffic flow bottlenecks at corridor on-ramps, but some secondary impacts may occur at other ramps within a corridor.

3.4.2.3.6.1 Simple Highway Corridor - Full Market Penetration of CAVs

The effectiveness of the proposed optimal coordination framework was assessed on a highway corridor (2.5 km long) with two on-ramps and one off-ramp (Figure 3-119) modeled in Vissim. The authors implemented the optimal coordination framework and simulated the corridor considering 0% (baseline) and 100% (optimal) CAV market penetration. Human driver behavior in the baseline scenario was simulated using the Wiedemann car-following model included in Vissim. The desired speeds in the CZ for on-ramps 1 and 2 were set to 50 km/h and 60 km/h, respectively. The traffic demand for the main road and on-ramp 1 was set to 1,400 veh/h, and three different traffic demands were considered for on-ramp 2: 1,200 veh/h, 1,500 veh/h, and 1,800 veh/h. Finally, the exit rate of vehicles on the off-ramp was set to 30% of the main ramp volume.

The average fuel economy and travel time results are shown in Figure 3-120. By following the optimal control inputs, the vehicles followed smoother acceleration patterns and avoided the frequent stop-and-go driving commonly observed in baseline scenarios when the on-ramp vehicles attempt to merge onto the main road. The optimal coordination mitigated the traffic jam propagation, leading to travel time savings of up to 40% and improvements in fuel economy of up to 55% over the non-coordinated scenario, as shown in Figure 3-120.

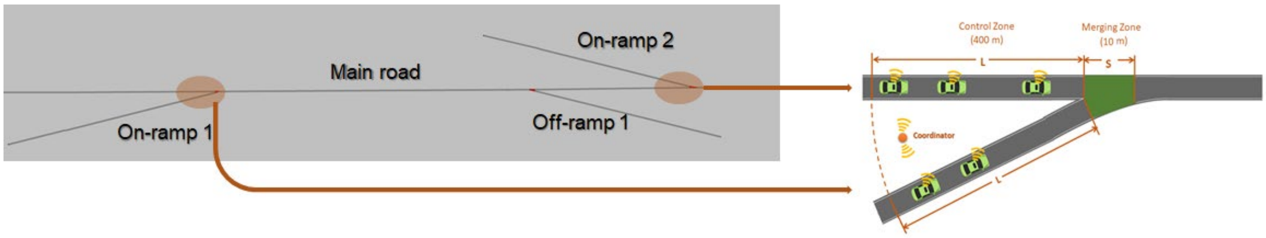


Figure 3-119. Simulated highway scenario.

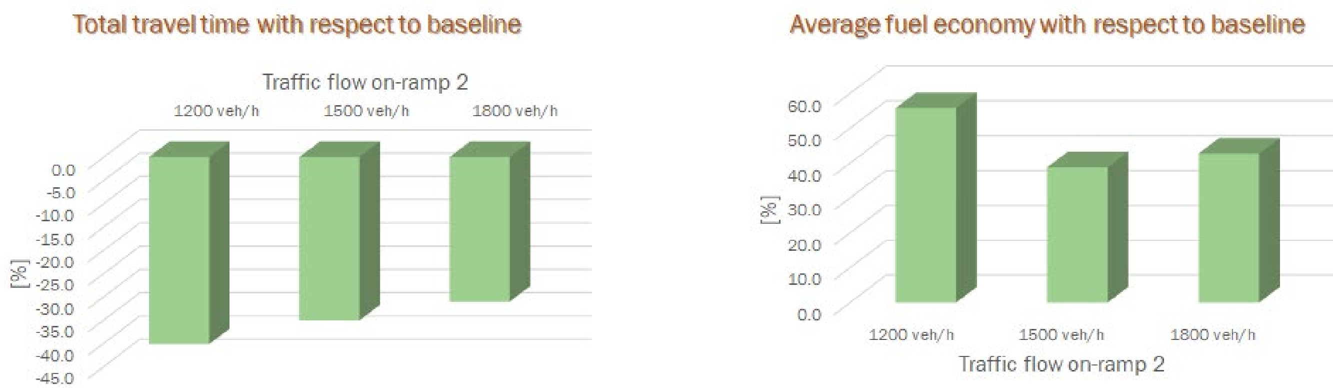


Figure 3-120. Average fuel economy and travel time results for the simulated highway corridor (2.5 km).

3.4.2.3.6.2 Simple Highway Corridor - Partial Market Penetration of CAVs

The simple corridor implemented in Vissim (Figure 3-119) was used to test the operational performance of the optimal controller in mixed traffic. The longitudinal driving behavior of humans in the baseline scenario was simulated with the psycho-physical driver behavior model developed by Wiedemann.[177] Simulations were conducted using fixed traffic demands for main and ramp roads of 1,200 veh/h, 1,000 veh/h, and 600 veh/h. A fixed 90%:10% ratio was assumed for LDVs:HDVs and different penetration rates (0%, 60%, and 80%) of optimally coordinated light-duty CAVs were used. The penetration rates of heavy-duty CAVs was assumed to be 100% (10% of the vehicles in the traffic network were assumed to be connected and automated trucks). The exit rate at the off-ramp road was set at 30% of the traffic flow. The spatiotemporal distribution plots for mean speed are shown in Figure 3-121. In the baseline case (Figure 3-121 top), the main road vehicles reduced their speed to below 30 km/h near the two merging zones. The worst traffic congestion was observed on ramp 1, where the vehicles approaching the merging zone performed stop-and-go driving while trying to find a safe gap into which to merge. This erratic behavior propagates up the ramp, slowing down the throughput. In contrast, by introducing high penetrations of optimally coordinated light-duty CAVs (i.e., 60% and 80%), the mean speed increased on ramp 1. Nevertheless, some effects were observed on the main road and ramp 2 where the average speed was slightly decreased.

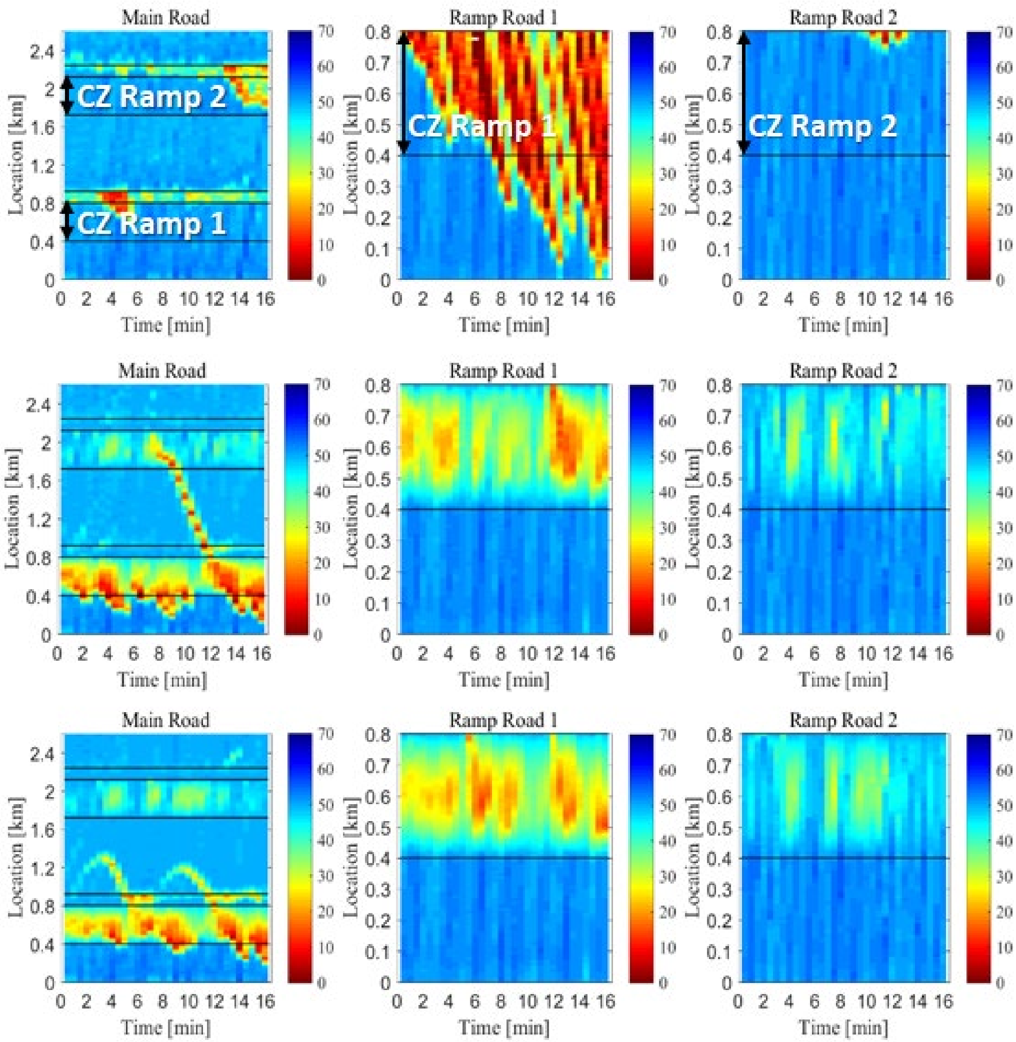


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Figure 3-121. Spatial-temporal distribution of mean speed plots of main and ramp roads. Top: 0%, middle: 60% and bottom: 80%.

3.4.2.3.7 Optimal Coordination for a Real-world Corridor Segment (I75 corridor)

- Optimally coordinated CAVs in the realistic corridor scenario exhibited the ability to enhance traffic flow and improve overall corridor fuel consumption across all levels of CAV penetration.
- At 100% penetration of CAVs, the optimal coordination framework provided a 7% reduction in overall corridor fuel consumption.
- At lower penetration levels, the coordination framework still achieved a significant benefit to overall corridor fuel consumption reduction. For example, at 20% CAV penetration, a fuel consumption reduction of 4% was achieved.

Based on traffic data availability, the authors modeled a 6.9 mi segment of the I-75 corridor in Vissim (Figure 3-122) and calibrated it to resemble real traffic conditions. The longitudinal driving behavior of humans in the baseline scenario was simulated with the psycho-physical driver behavior model developed by Wiedemann. Traffic data, including volume, speed, and on/off ramp traffic, were obtained from the Tennessee Department of Transportation's traffic sensors and cameras. These data were then used to calibrate vehicles' speed distributions as the measure of effectiveness, considering a 1 h period. The Vissim model was calibrated so that vehicles' speed distribution in the simulation model was comparable to the field observations.

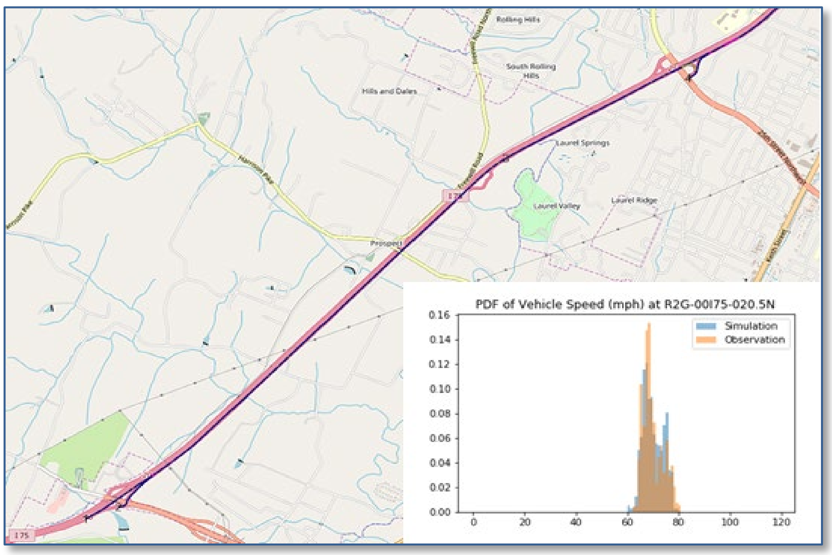

Figure 3-122. Corridor modeled in VISSIM and histogram of observed vs simulated vehicle speeds in the 20.5 N mile marker.

As part of the calibration process, the authors used the Latin hypercube design, a design of experiment sampling method, to select 100 comprehensive parameter sets for the initial calibration. Each parameter set was simulated in Vissim with a different random seed. Results based on these simulation settings, in terms of vehicle traveling speeds and the observed speeds from radar sensor data, are shown in Figure 3-122 (bottom right corner). The average traffic demand for the main and ramp roads was set to 2688 veh/h, 1400 veh/h, and 771 veh/h. The simulation time was set to 1,200 s.

The impacts of optimal CAV coordination were assessed considering the current day fleet distribution scenario defined in the SMART Mobility Modeling Workflow Capstone Report. Eight MPRs were studied, as defined in Table 3-15. The percentage of electrified vehicles for the chosen fleet distribution scenario was <2%.

Table 3-16. Market penetration rates considered for assessment.

Scenario	Baseline	2	3	4	5	6	7	8
% Light-duty CAVs	0	0	5	10	20	50	80	100
% Heavy-duty CAVs	0	100	100	100	100	100	100	100

The fuel savings shown in Figure 3-123 increased steadily with increased penetration when more than 10% of the vehicles on the road were CAVs. The increase reached a maximum of about 7% at full CAV MPR. Although electrified vehicles were considered in this work, the sample size was too small; thus there were not statistically significant data from which to draw generalizable conclusions. Additional scenarios could be run with larger samples of electrified vehicles to investigate overall trends.

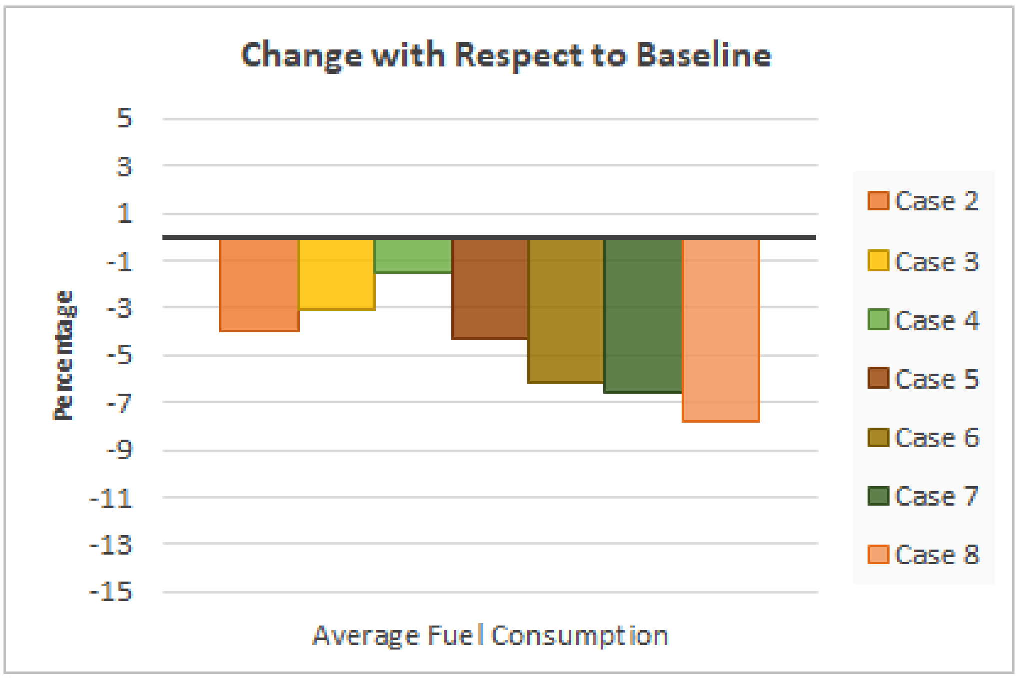

Figure 3-123. Fuel consumption results for the current time fleet distribution scenario.

The available traffic data was more representative of free flow conditions and light traffic, and, as such, the benefits of applying coordination will be moderate. Future work could consider additional baseline scenarios for an intra-city corridor under different traffic conditions (i.e., from moderate to heavy congestion) to get more insights into the full range of benefits attainable through coordination. A need also exists to find better ways to quantify the direct benefits of coordination in interconnected scenarios and to explore how far upstream and downstream from the merging point traffic is affected/improved by the coordination itself. Corridors with shorter segments between on-ramps may render higher percentages of improvement under similar traffic conditions if the same metrics used here are applied. This could occur because (1) the percentage of the road over which the vehicles are optimally controlled will be larger with respect to the entire corridor, and (2) the effects of the merging vehicles on the main road's upstream traffic will be more prominent in the baseline and low penetration scenarios than the other scenarios.

3.4.3 Regional Level Strategies for CAV Impact Mitigation

- Transit ridership in Bloomington, IL could be increased by 11% by subsidizing ride-hailing access to transit stops, decreasing overall fuel use by 1.1%
- ZOV pricing of $0.33 per mile would reduce overall ZOV miles by 25%, helping to mitigate the potential impacts of widespread private AV adoption
- Coordinated platooning with high wait times can increase the total time that vehicles spend in platoons, but only leads to moderate energy savings due to issues with platoon formation

As discussed earlier in Section 3.3.2, high levels of vehicle automation can possibly lead to increased overall energy consumption within a region, due to significantly elevated VMT and possibly more congestion due to the overall number of additional trips enabled by automation. Fully automated driverless vehicles are particularly susceptible to these increases in VMT and were shown to enable certain scenarios of greatly elevated VMT and thus increased energy usage. While the vehicle optimal control strategies employed in the preceding section offer some solutions at the vehicle-to-corridor level, this section seeks to highlight some of the regional level strategies investigated to mitigate some of the less desirable aspects of certain future highly automated vehicle use cases. The study results shown below are not intended to cover all possible mitigation strategies, but rather to highlight some of the promising options uncovered and evaluated within this work.

3.4.3.1 Low-Cost Ride-Hailing Access to Transit

- Transit ridership in Bloomington, IL could be increased by 11% through subsidizing ride-hailing access to transit stops, decreasing overall fuel use by 1.1%

One of the mitigation strategies looked into the impact of providing very low/no cost ride-hailing trips to public transit stops/terminals to facilitate transit access for travelers. Utilizing the same Bloomington Illinois region discussed in the earlier implications section (3.3.2.2), a study investigated the regional changes when ride-hailing drop-offs at bus stops were provide at zero cost. In this scenario, overall transit ridership was increased by 11%, with a resulting 1.4% decrease in overall VMT and 1.1% decrease in overall fuel use, suggesting that providing very low cost transit access (likely enabled by CAV technologies) can provide some regional benefits relative to overall energy use. Additionally, these free transit-access rides appear to offer some travelers in outlying regions increased access to transit, with additional benefits related to overall productivity and access to jobs.

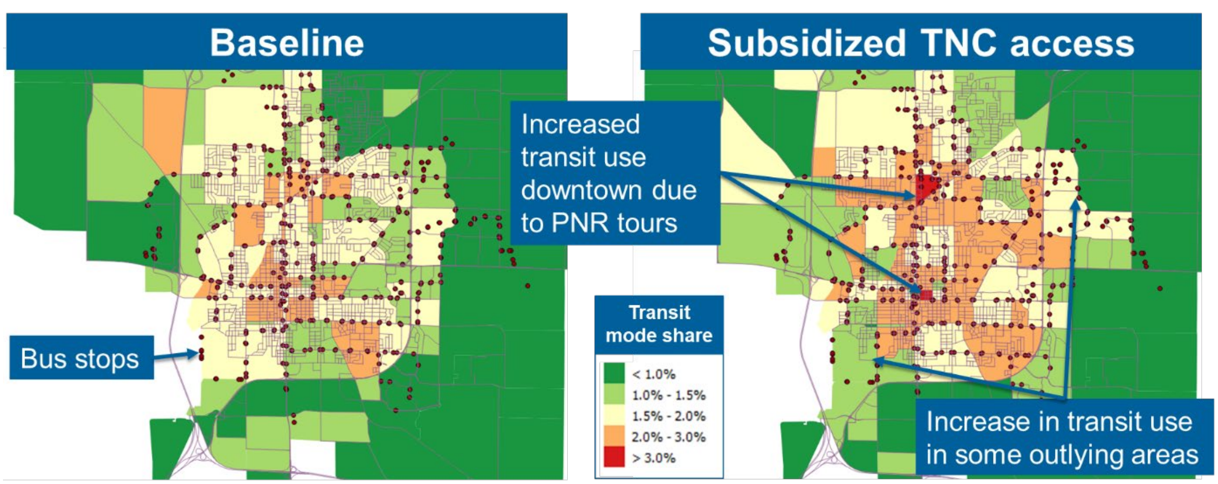

Figure 3-124. Bloomington Illinois zero-cost ride-hailing transit access study overview.

3.4.3.2 Zero Occupancy Vehicle Pricing

- VOZ pricing of $0.33 per mile would reduce overall ZOV miles by 25%, helping to mitigate the potential impacts of widespread private AV adoption

Given that ZOV operation is one of the main drivers of the elevated VMT in several of the highly automated future scenarios investigated for this work[178], a strategy of pricing zero occupancy vehicle miles at a rate of $0.33 was investigated as a possible lever to perhaps mitigate some of the increased VMT due to high levels of automation. Depending on the penetration of AVs, the $0.33/mile ZOV charge shows a very significant — approximately 25% — reduction in ZOV miles traveled for both high (65%) and low (37%) AV penetration scenarios run for the Bloomington area in POLARIS. This ZOV VMT reduction corresponds to an overall reduction in VMT of up to 4%, as shown in Figure 3-125.

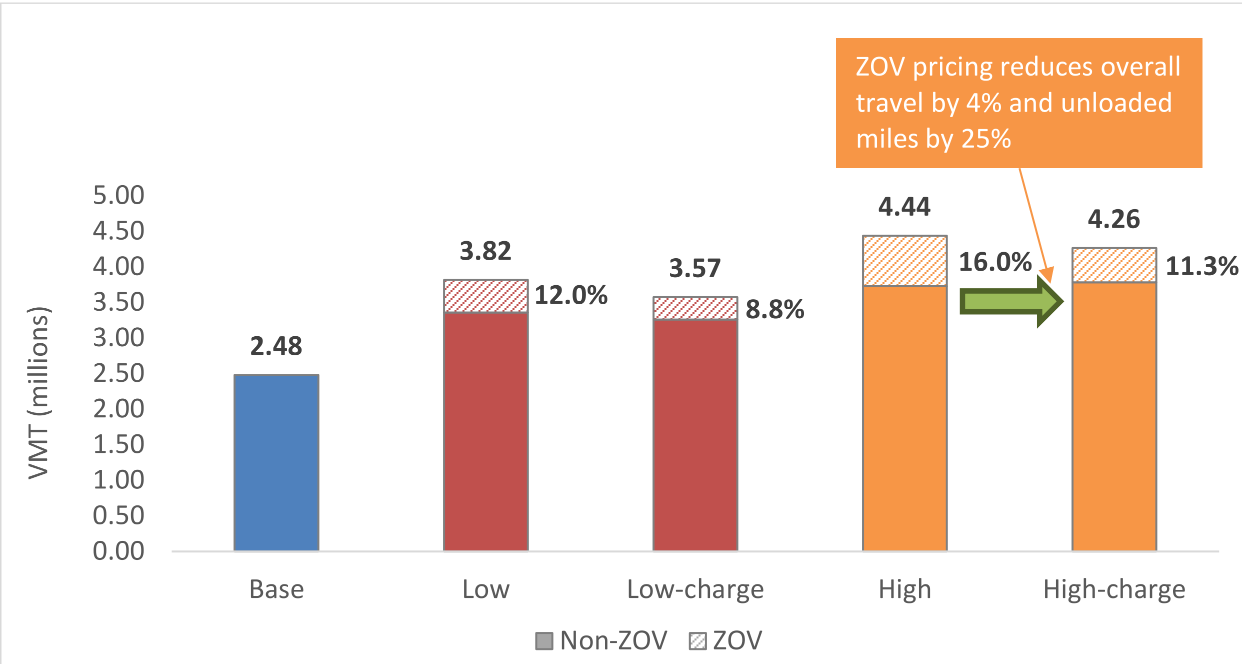

Figure 3-125. Summary of ZOV scenarios (low and high AV penetration) and the associated impacts of a ZOV per-mile charge.

3.4.3.3 Coordinated Platooning

- Coordinated platooning with high wait times can increase the total time that vehicles spend in platoons, but leads to only moderate energy savings due to issues with platoon formation.

One of the expected benefits of AVs is their platooning capabilities; however, vehicle platooning has been studied mainly in terms of single platoons. To analyze the energy impact(s) of coordinated platooning vehicles at the regional level, i.e., modifying trajectories and departure times for many vehicles to increase time spent in a platoon, an optimization model developed by Argonne researchers was adopted.[179] The optimization model schedules platoons' formation and dissolution given the demand for vehicle travel. To correctly simulate the platoons' movements, the POLARIS code was updated to accommodate changes in travel times and trajectories. POLARIS was first manually linked to the optimization model (involving many pre- and post-processing steps), and then it was enhanced so it would automatically and continuously call the optimization model (with the POLARIS vehicles' trajectories as inputs) and also update their movements according to the optimization model results. Because optimization models are computationally intensive and tax computing resources, a clustering algorithm was also developed to group vehicles into multiple bins and thereby improve performance. This approach breaks the big problem into smaller ones, which, in turn, reduces the size of the optimization model problems and improves performance. In addition, Autonomie was updated to take into account the reduction in energy consumption attributable to the reduction in aero drag on vehicles in platoon. Two case studies were conducted for a sample of the Detroit region in addition to the Bloomington, Illinois, analysis (shown in Table 3-17).

Table 3-17. Bloomington, IL, mobility and energy impacts from platooning at low penetration rate.

Wait Time (second)	No Platoon	300	600
Total Trips	452,873	453,555	456,580
% of platooning capable trips	-	35.3%	35.3%
% of Platooning trips	-	2.6%	4.5%
Total VMT	1,938,903	1,936,901	1,947,523
%VMT in Platoon	-	1.3%	2.6%
Fuel Consumption(kg)	152,83,	151,950	151,220
Fuel Consumption per mile(gr/mile)	78.8	78.4	77.6

Preliminary results indicate that with increases in wait times, the chances for platooning to occur increase significantly. In addition, given the assumptions and models used for estimating the reduction in drag coefficients, the savings in energy consumption increases by 0.5% and 1.5% for 60-second and 200-second wait times, respectively. With a wait time of 600 seconds, 4.5% of all trips and 2.6% of all miles could be platooned, leading to a fuel savings of 1.0%, with some of the in-platoon fuel savings offset by platoon formation factors, as the car waits to join and accelerates to join the platoon.

4 Summary and Conclusions

Dedicated to furthering the understanding of the energy implications and opportunities of advanced mobility technologies and services, the U.S. Department of Energy's Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium was formed to create tools and generate knowledge about how future mobility systems may evolve and how these evolutions will impact overall mobility, energy, and productivity. Specific to the efforts described in this report and in support of the Connected and Automated Vehicle (CAV) Pillar of the Consortium, this report detailed research, development, and analysis to identify the energy, technology, and usage implications of connectivity and automation and develop efficient CAV solutions at a range of scales. To address these goals, the Pillar used a broad and multidisciplinary approach, utilizing wide-ranging experimental testing, mobility-centric model expansion and development, advanced controls and optimization at the vehicle-to-regional level, and a range of newly developed and more traditional analytical approaches. Experimental results and insights described in this report span both heavy-duty and light-duty vehicles and employ a mix of laboratory, track, in-field, and large-scale fleet data collection and experiments. The CAV-specific modeling adaptations and expansions discussed in these efforts build upon more than 15 years of modeling and simulation expertise within the DOE and integrate DOE's high-fidelity and validated modeling tools and approaches with state-of-the-art CAV data, capabilities, and controls. The simulation and controls efforts investigated CAV technologies at the vehicle-level, corridor-level, regional-level, and national-level in terms of both the implications related to introducing CAVs technologies into current transportation systems as well as an evolving transportation ecosystem that can directly leverage the new information, connectivity and/or automation afforded by connected and automated mobility technologies to reduce energy usage and improve mobility. Since the transition to a highly connected and automated transportation future will not be overnight, the Pillar's simulation and controls efforts spent particular attention on assessing impacts and developing controls for mixed traffic environments with varying penetrations of manually and automatically driven vehicles.

The CAVs Pillar sought to answer three major questions regarding CAVs technologies and their implications as well as provide a synthesis of both internal and external new and emerging research findings related to CAVs and their subsequent impact at a range of scales. This section summarizes the primary research results and insights from the CAVs Pillar, addressing each of the research questions posed in the introduction. It is expected that these results will be beneficial to a range of stakeholders including transportation system planners, mobility engineers, vehicle developers, and the transportation research community at-large.

A common theme observed across multiple research insights created from this work is that CAV technologies offer a significant potential for improving vehicle-level efficiency, yet if higher-level coordination is not properly implemented in a given strategy or technology these benefits may not be seen at the corridor level or regional level. For example, several studies within this report describe strategies and technologies that may increase overall system-level consumption despite reducing individual-level energy consumption due to creating instabilities and larger disturbances for other vehicles operating in the surrounding environment. With this issue in mind, many of the findings in this report strongly suggest a systems-centric approach is necessary to more robustly identify energy savings opportunities that are applicable across multiple scales. Further expanding on this insight, another significant high-level conclusion from these efforts suggests that the promising strategies and technologies utilized for increased vehicle-level and transportation-level efficiency are at risk of being negated by an increase in overall miles traveled, due to possible rebound effects (driving more because connectivity and/or automation makes it easier and/or cheaper) as well as new usage cases associated with widespread connectivity and automation

4.1 Summary of Findings and Their Implications

4.1.1 How will connected and automated vehicles and systems behave in the real world?

The results and data provided by the Consortium's efforts relative to experimentally derived Class-8 truck platooning impacts are one of the most comprehensive and rigorous investigations of platooning energy consumption to date. The average savings across a three-truck platoon under realistic operating conditions was found to be between 5% and 13% depending on the gap distance between vehicles. For a two-truck platoon, the average saving was found to be between 2% and 5%, again depending on the gap between vehicles. Combining a national-level assessment of platooning opportunities discussed in this report with the experimentally observed fuel savings potential suggests that truck platooning could be an effective fuel saving strategy nationally. Platoons of three close-following trucks achieving a combined 13% fuel consumption reduction could save up to nearly 2.1 billion gallons of fuel per year – a 7% reduction in heavy duty fuel use.

The CAVs Pillar's experimental efforts also investigated the fuel consumption sensitivities and specific electrical loads associated with the sensing, processing, and actuation systems of automation systems. Laboratory-based testing of select vehicles supplemented with additional publicly available test data for a wide range of MY2019 BEVs and ICE-based vehicles found that the energy consumption sensitivities related to electrical loads vary significantly depending on cycle average power consumption and the type of driving where they are applied. More aggressive driving showed a lower impact relative to a given additional electrical load, whereas driving with a significant portion of idling was particularly strongly impacted. For example, a 2000W additional load showed overall real-world increases in consumption ranging from 17% to 30% for BEVs, yet if this load was applied over the UDDS cycle (a lower power, increased idle percentage cycle), the consumption increase was 38% to 70%. Experimental testing also observed real-world, in-use electrical loads associated with AV systems for two different AV technologies. Field testing of a Cadillac CT6 with Super Cruise, a L2+ automation system, found automation system loads of 101-104W during on-road usage. Interestingly, the CT6's overall electrical loads changed minimally when Super Cruise was deactivated, suggesting that for lower-level automation capabilities, the true electrical load penalty associated with certain automated eco-driving capabilities may be minimal if these systems are already in use as part of safety features. Field testing of an automated vehicle prototype, provided by an industrial project partner, found automation loads ranging between 300W and 400W for functionalities including hands-free highway operation (L3) and fully self-driving operation and navigation at lower speeds (L4). While the loads required for true driverless vehicle operation across a wide range of Operational Design Domains are still subject to significant uncertainties due to the rapid pace of vehicle development and refinement, the experimentally observed electrical load levels discussed in this report suggest that many of the capabilities related to automated eco-driving may be implementable at electrical loads ranging from 100W to 400W, depending on the required capabilities.

Large-scale light-duty fleet data collection and analysis efforts undertaken within the CAV's Pillar also highlighted the real-world opportunities and impacts of several CAV functionalities. In partnership with Volvo Cars and their DriveMe study of ACC vehicles operating in Gothenburg, Sweden, the pillar found that, at the individual-vehicle level, ACC-operating vehicles consumed 5%–7% less fuel than the manually driven vehicles operating within the same designated driving network. It is important to recall that gains on the individual level do not necessarily translate to overall system improvements, but this individual-vehicle level data still serves as an important validation of the possible opportunities for AVs to reduce energy consumption.

Leveraging data from 45,000 actual light-duty vehicle trips, the CAVs Pillar also found that a "green-route" (algorithmically creating a more efficient route for a given destination) existed for about one-third of all trips evaluated. These more efficient routes provided, on average, 12% lower energy consumption versus the originally selected route. Interestingly, roughly half of the "greenest" route alternatives in the study also had lower travel times, suggesting a "double win" of both faster and more efficient travel.

4.1.2 What are the implications of connectivity, automation, and connectivity combined with automation as applied to current and near-term transportation systems?

A major insight from these efforts is the differentiation between connected and automated technologies and "autonomous" systems (i.e. an automated vehicle with no connectivity). For example, at the freeway corridor level, automation without V2V connectivity applied to the current transportation system may lead to more congestion and increased consumption due to traffic instabilities created by the unconnected automation systems and lack of information from surrounding vehicles. In contrast, cooperative operation enabled by both automation and connectivity (V2V in this case), shows increasing benefits to both congestion and energy consumption as market penetration of the enabled vehicles increases, ultimately removing most if not all traffic congestion at current demand levels.

At the regional level, fully automated, privately owned vehicles, if introduced into our near-term transportation system, have the potential to substantially impact traffic and energy use through induced demand and zero occupancy vehicles (ZOV), which travel empty due to vehicle repositioning. Regional-level modeling based in Bloomington, IL, done within the CAVs Pillar indicates that that the presence of fully automated privately owned vehicles would increase trips more than 27% (at low penetration rate/high cost) and 39% (at high penetration rate/low cost). With the combined effect of ZOV travel, this would increase system level VMT by 42% and 63%, respectively. Relatedly, these findings and other regional-level modeling results from the CAVs Pillar also show that value of travel time (VOTT) is a critical parameter for understanding and assessing the outcomes of CAVs technologies since as VOTT is reduced (via higher levels of vehicle automation or other means), significant travel increases can occur.

While efforts within the CAVs pillar found methods to directly expand regional-level simulations to national-level estimates of CAV impacts difficult and not necessarily robust, a range of high-level analyses provided insights into the complex landscape faced by increased CAV adoption and development. While CAVs appear to provide an appealing set of characteristics to a range of consumers and manufacturers, the dynamics of their long-term integration and adoption into the larger mobility and transportation market place is still filled with considerable uncertainties.

4.1.3 What is the best way to harness CAVs for reduced energy use and improved mobility in transportation?

Building upon the modeling efforts discussed above, the CAVs Pillar explored how vehicle controls, active traffic management, connectivity, optimized vehicle coordination, and regional level strategies can be used to capitalize on CAVs technology to reduce energy use and improve mobility in a transportation system. At the individual vehicle level, a large-scale study of advanced vehicle controls for a range of powertrain types and usage scenarios showed that automation and connectivity combined with energy-focused control results in significant energy/fuel consumption savings of up to 22% for internal combustion engine vehicles. These results are highly dependent on the type of road and scenario in which the controls are applied, with highway showing a 6% improvement in contrast to the city's 22%. Vehicle-to-infrastructure (V2I) connectivity enables better knowledge of a vehicle's future horizon and can improve the performance of the controls optimization, especially the eco-driving strategies that incorporate detailed powertrain information.

At the corridor level, active traffic management strategies and optimized coordination were also shown to enable opportunities for improved traffic flow and reduced energy use. Specifically, results from this report regarding connectivity enabled active traffic management strategies showed improved traffic flow even for low market penetrations of CAV technologies. Similarly, the developed optimized coordination algorithms for automated vehicles were also shown to be effective at improving overall corridor efficiency and mobility at penetration levels as low as 20%. At full market penetration of CAVs, increased efficiency and mobility benefits can be observed while also enabling new opportunities for more active intersection and corridor control.

At the regional level, a range of mitigation strategies were identified and assessed to offset some of the less desirable high-level impacts of CAV technologies that can increase energy usage. Strategies developed and assessed include ZOV optimization, improved transit access, leveraging connectivity and automation for improved situational awareness, and large-scale traveler coordination. Strategies identified to be particularly effective included subsidizing ride-hailing access to transit stops, as well as modifying ZOV pricing to incentivize more intelligent vehicle-sharing and route planning. Interestingly, coordinated platooning with high wait times (to allow for larger platoons to form) can increase the total time that vehicles spend in platoons, yet may only lead to moderate energy savings due to issues with platoon formation dynamics.

4.2 Recommendations for Future Work

Within both the private and public sector, significant funding is being directed towards large-scale implementation and development of connectivity and automation related technologies in the form of new prototypes, products, test beds, and commercial-scale projects. Many municipalities, states, and regional coalitions are beginning to develop and operate large-scale connected and situationally aware roadway systems along major corridors and roadways and these real-world applications offer a strong motivation for continued data collection and experimentation to gain real-world insight and provide updated validation data for improved modeling capabilities. Relatedly, connectivity and automation technologies continue to become more available to consumers and fleets, thus additional data-collection and experimental efforts are also suggested. Given the rapid pace of technology developments in the mobility industry in general, it is crucial that DOE continues to investigate and support the creation of real-world data regarding state-of-the-art technologies and transportation system solutions. Furthermore, a range of emerging technologies, such as aerial and ground-based delivery drones, micro-mobility vehicles, and last-mile focused good transport vehicles are being introduced into the marketplace; these vehicles represent a dramatic expansion of what a vehicle can and may do within a mixed freight and personal mobility system.

While these efforts did address some of the synergies between vehicle electrification and CAV technologies, much more work could be done to more deeply assess additional opportunities for electrified, connected and automated mobility solutions and to study the impact sensitivities of these technologies. Additionally, scenarios considering short term and long term vehicle fleet distributions and their associated efficiency characteristics could be analyzed to better understand the potential benefits and sensitivities of coordination in the future. Building on the foundational efforts in this report, future work could also more deeply investigate the benefits of integrating human behavior predictions and how to enhance interactions between human drivers and CAVs in an overall optimization framework. Better understanding of human behavior would also likely reduce some of the uncertainties found under low market penetration rates within these efforts. Furthermore, additional work could be done to better understand the implications of more broadly applied optimal coordination with vehicle actively changing lanes, creating openings for other vehicles and actively managing traffic flow within a large corridor.

Future work could also consider additional baseline scenarios for intra-city corridor operations under a wider range of natural traffic conditions. This would allow for more insights into the full range of benefits attainable through coordination as well as more robust benefits across a larger range of expected operational environments. There is also a need to find more strategies and methods to quantify the direct benefits of coordinating larger interconnected scenarios and explore how far upstream and downstream from a control point traffic is affected or improved by coordination. Similarly, validating the behaviors and insights described in these efforts through additional field studies and data collection activities would strengthen the overall body of knowledge and further validate the modeling approach and tools developed in this effort. Lastly, expanding these efforts to additional geographic locations within the United States (including urban, suburban, and rural use cases) would further identify and support areas for continued DOE research, investigation, and validation.

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6 Appendices

6.1 Appendix A — CAV Scenario Generation Model

Table 6-1. CAV Deployment Mobility and Energy Results

Run	AV Penetration	VOTT Reduction	VMT (millions)	VHT (millions)	Avg. Travel Time (min)		Avg. Trip length (mi)
Base	0%	0%	268.0	8.17	23.4	11.79	Fuel Use (MM gallons)
0.2	36.1%	0%	291.2	7.86	22.2	12.50	**4.85**
0.3	75.5%	0%	292.0	7.96	22.5	12.73	**5.34**
1.1	10.1%	30%	306.5	8.37	23.7	13.38	**5.32**
1.2	36.1%	30%	324.6	9.04	25.5	14.21	**5.62**
1.3	75.5%	30%	337.7	9.64	27.3	14.82	**5.94**
2.1	10.1%	50%	319.2	8.74	24.7	13.99	**6.14**
2.2	36.1%	50%	357.8	10.45	29.9	15.77	**5.85**
2.3	75.5%	50%	387.4	11.92	34.5	17.40	**6.55**

Table 6-2. Within-Household AV-Sharing Results

Unserved Trips	Scenario 1 Flex = 0 min		Scenario 2 Flex = 5 min		Scenario 3 Flex = 10 min		Scenario 4 Flex = 15 min		Scenario 5 Flex = 20 min	
0	1,220	37%	1,420	43%	1,609	49%	1,740	53%	1,887	57%
1	1,107	33%	1,053	32%	1,002	30%	972	29%	900	27%
2	661	20%	583	18%	496	15%	437	13%	394	12%
3	193	6%	171	5%	149	5%	115	3%	90	3%
4	78	2%	51	2%	36	1%	34	1%	30	1%
5	33	1%	24	1%	14	0%	8	0%	5	0%

Unserved Trips	Scenario 1 Flex = 0 min		Scenario 2 Flex = 5 min		Scenario 3 Flex = 10 min		Scenario 4 Flex = 15 min		Scenario 5 Flex = 20 min	
6	13	0%	4	0%	1	0%	1	0%	1	0%
7	1	0%	2	0%	2	0%	2	0%	3	0%
8	3	0%	2	0%	1	0%	1	0%	0	0%
9	1	0%	0	0%	0	0%	0	0%	0	0%
Total Unserved Trips	3,603		3,110		2,683		2,395		2,130	
Reduction%	0		-14%		-26%		-34%		-41%	

Table 6-3. Comparison to baseline for Level 4 and 5 CAVs for various fleet assumptions

	Impacts of population growth				Impact of vehicle technology on fuel use (gallons)					
					Tech-low			Tech-high		
Scenario	**Trips**	**VMT**	**VHT**	**Avg. Speed (**	**600W[1]**	**1000W**	**2500W**	**600W[1]**	**1000W**	**2500W**
Baseline (2015)[2]	475,149	1,645,855	63,178	26.1	64,428			64,428		
2025_base	523,806	1,851,744	71,440	25.9	48,259			34,530		
2040_base	563,131	2,004,973	80,090	25.0	31,493			11,243		
(% Δ from 2015 baseline)	**Impacts of level 4 CAV**				**Impact of vehicle technology on fuel use (gallons)**					
					Tech-low			**Tech-high**		
Scenario	**Trips**	**VMT**	**VHT**	**Avg. Speed (**	**600W[1]**	**1000W**	**2500W**	**600W[1]**	**1000W**	**2500W**
2025_base	10%	13%	13%	-1%	-25%			-46%		
2025_cav-low	11%	16%	11%	5%	-22%	-22%	-19%	-43%	-42%	-40%
2025_cav-high	11%	20%	14%	6%	-19%	-17%	-12%	-41%	-40%	-34%
2040_base	19%	22%	27%	-4%	-51%			-83%		
2040_cav-low	20%	32%	31%	1%	-46%	-45%	-41%	-80%	-80%	-77%
2040_cav-high	20%	36%	37%	0%	-43%	-41%	-33%	-79%	-78%	-74%
(% Δ from 2015 baseline)	**Impacts of level 5 CAV**				**Impact of vehicle technology on fuel use (gallons)**					
					Tech-low			**Tech-high**		
Scenario	**Trips**	**VMT**	**VHT**	**Avg. Speed (**	**600W[1]**	**1000W**	**2500W**	**600W[1]**	**1000W**	**2500W**
2040_cav-low	46%	64%	86%	-12%	-32%	-30%	-23%	-74%	-73%	-69%
2040_cav-high	58%	85%	120%	-16%	-22%	-19%	-6%	-69%	-67%	-60%
2040_cav-low-ZOV charge	44%	61%	80%	-11%	-33%	-31%	-24%	-75%	-74%	-70%
% Δ from 2040_cav-low	*-1%*	*-2%*	*-3%*	*1%*	*-1%*	*-2%*	*-2%*	*-4%*	*-4%*	*-4%*
2040_cav-high-ZOV charge	54%	79%	112%	-15%	-24%	-21%	-9%	-71%	-69%	-62%
% Δ from 2040_cav-high	*-2%*	*-3%*	*-4%*	*1%*	*-3%*	*-3%*	*-3%*	*-5%*	*-5%*	*-5%*

1. CAV accessory load is 0 for the baseline cases
2. Vehicle low tech and high tech scenarios are the same for baseline

6.2 Appendix B — CAV Scenario Generation Model

Appendix material on the CAV Scenario Generation model (described in Section 3.3.3):

The following summaries describe methodological approaches for the structural elements or modules that compose the CAV Scenario Generation model:

- *Population* tracks population growth trends and shifts in preferences for various CAV and non-CAV concepts for each population cohort. Population growth differentially increases the number of persons in each cohort, aging of the population may shift persons between cohorts (depending on the age dependence of cohort membership), and changes in cohort members' utilities for the various travel concepts alters the fraction of the cohort that uses each travel concept.
- *Activities* tracks activity patterns and their changes resulting from consumer choice, population shifts, latent demand for each population cohort, CAV/non-CAV concept, and trip purpose. In addition to accounting for the shift in number of activities caused by changes in the population and their choices of travel concepts, the realization of latent demand may increase the overall number of activities performed by cohorts. Locations of activities can be considered to change only in a general sense that cohorts can be defined to have a geographic element, such as urban core or suburban.
- *Energy* tracks energy use by the CAV/non-CAV concept, population cohort, and trip purpose. The energy consumption of each vehicle type results from its frequency of use, its fuel efficiency, and the distance traveled per activity.
- *Travel Choice* models traveler choice of the CAV/ non-CAV concept using a logit formulation. Utilities for the travel concepts within each cohort depend on the capital and operating costs for travel, the time taken, vehicle occupancy, and demand for travel.
- *Travel Time and Distance* track vehicle and traveler distance and time traveled, accounting for deadheading and total vehicle occupancy. Each activity in each cohort is realized using the cohort's distribution of travel concepts.
- *Infrastructure* models the allocation of infrastructure investments and their effect on the availability of CAV concepts, on travel distances, and on travel times. Infrastructure investments draw on an annually replenished fund that is allocated to travel concepts based on the remaining infrastructure to be built in support of those concepts and upon the relative value of such improvements.
- *Vehicles and Vehicle Requirement* track vehicle stock for the various CAV/non-CAV concepts, including changes resulting from new vehicle sales, used vehicle sales, and hardware/software upgrades to vehicles. In addition to altering vehicle quantities resulting from purchases and retirement/salvage, vehicles may be sold by members of one cohort to members of another or may be upgraded from one CAV concept to a more advanced one.
- *Manufacturers* models research and development (R&D) investment in CAV concepts and cost reductions in vehicle technologies. Costs for CAV concepts decay exponentially toward an asymptote, but at a rate determined by investment in R&D, which is in turn dependent on prospective adoption of the CAV concept.
- *Regulators* models the regulatory workflow required for use of CAV concepts. A fixed annual capacity for regulation may limit the rate at which new CAV concepts are approved for general use.
- *Insurers* models insurance premiums and payouts for CAV/non-CAV concepts, including the influence of safety and incidents. Insurance rates for different concepts depend on their incident rates and the funds available in an insurance pool, but rates are adjusted for the use of new CAV technologies and underwriting is only available after sufficient on-road experience.

- *Safety* tracks real and perceived safety benefits of CAV concepts. Safety benefits are tracked in addition to the cost of incidents.

The developed systems simulation provides detailed multi-dimensional time-series outputs for the key variable in each module, including time series of technology adoption and outcomes, stakeholder actions, and timing and characterization of bottlenecks at stage gates. The time series of CAV adoption and outcomes include CAV concept share, activity counts, vehicles (sales, resales, retrofits, and stock), time and distance traveled, and energy use. Each of these series spans 2020 through 2050 for each traveler cohort, traveler activity, and CAV concept. Stakeholder actions include manufacturing R&D and technology cost reduction associated with R&D and learning-by-doing, as well as infrastructure development.

Table 6-4. Sensitivity ranges for variables in the three CAVs Scenario Generation studies

Variable	Range in Screening Study	Range in Energy Study	Range in Comprehensive Study
Value of time	$4/hr to $60/hr	$4/hr to $60/hr	$4/hr to $60/hr
Multiplier for cost of insuring CAVs	50% to 200%	Not varied	50% to 200%
Accident rate of CAVs relative to L0	20% to 200%	Not varied	20% to 200%
Consumer utility for using CAVs	-$10,000 to +$40,000	-$10,000 to +$40,000	-$10,000 to +$40,000
Variable cost of using CAVs relative to L0	-$0.50/mile to +$1.50/mile	-$0.50/mile to +$1.50/mile	-$0.50/mile to +$1.50/mile
Minimum cum. travel prior to insurance underwriting	10^8 miles to 109 miles	Not varied	10^8 miles to 109 miles
Rate of CAV cost reduction	0%/year to 20%/year	0%/year to 20%/year	0%/year to 20%/year
Initial infrastructure readiness for L4	50% to 100%	50% to 100%	0% to 100%
Fraction of passenger time freed by L4	50% to 100%	50% to 100%	40% to 90%
Valuation of safety by CAV-averse travelers	100% to 1000%	Not varied	100% to 1000%
Valuation of safety by CAV-prone travelers	10% to 100%	Not varied	10% to 100%
Multiplier for vehicle occupancy	Not varied	30% to 300%	30% to 300%

Variable	Range in Screening Study	Range in Energy Study	Range in Comprehensive Study
Multiplier for L4 deadheading	Not varied	100% to 200%	100% to 200%
Relative cost of transit to L0	Not varied	$0.25/mile to $3.00/mile	$0.25/mile to $3.00/mile
Relative cost of L0 taxi to L0	Not varied	$0.50/mile to $4.00/mile	$0.50/mile to $4.00/mile
Relative cost of non-vehicular replacements to L0	Not varied	-$10/mile to $0/mile	-$10/mile to $0/mile
Relative cost of automated highway	Not varied	Not varied	$0/mile to $3/mile
Multiplier for L4 fuel efficiency	Not varied	50% to 150%	50% to 150%

6.3 Appendix C — Detailed Optimal Control Problem Formulation for Eco-driving Algorithms

Table 6-5. Optimal control problem formulation for the speed-only and speed+powertrain eco-driving algorithms (detailed version of Table 3-10)

Optimization		Speed-only	Speed + powertrain		
Powertrain		Any	EV	ICEV	HEV
Control variables		Acceleration (a)	Gear shifting and braking force (γ_i, F_{b})		
			Motor torque (T_{m})	Engine torque (T_{e})	Motor + engine torque (T_{m}, T_{e})
Cost function to minimize		Acceleration "energy" $\int_{t_0}^{t_f} a^2\,dt$	Battery energy $\int_{t_0}^{t_{\mathrm{f}}} P_{\mathrm{bat}}(\gamma_i v, T_{\mathrm{m}})\,dt$	Fuel mass $\int_{t_0}^{t_{\mathrm{f}}} \dot m_{\mathrm{f}}(\gamma_i v, T_{\mathrm{e}})\,dt$	Equivalent energy consumption $\int^{t_{\mathrm{f}}} P_{\mathrm{fuel}}(\gamma_i v, T_{\mathrm{e}}) + \lambda_{\mathrm{E}} P_{\mathrm{bat}}(\gamma_i v, T_{\mathrm{m}})\,dt$
Subject to	System dynamics	Vehicle dynamics $\dot s = v,\ \dot v = a$	Vehicle dynamics including powertrain operation $\dot s = v,\ \dot v = m^{-1}[\gamma_i \eta T_d - F_{\mathrm{b}} - (c_0 + c_1 v + c_2 v^2 + mg\sin\alpha)]$		
			$T_d = T_{\mathrm{m}}$	$T_d = T_{\mathrm{e}}$	$T_d = T_{\mathrm{m}} + T_{\mathrm{e}}$
	State constraints	Preceding vehicle ($s(t) + s_d(t) - s_p(t) \leq 0$)			
		Speed limits ($v_{min}(s) \leq v(t) \leq v_{max}(s)$)			
	Interior-point constraints	Traffic signal phase and timing (SPaT) [when V2I enabled] ($s(t_1) = s_1, s(t_2) = s_2, \ldots, s(t_N) = s_N$, where N is the number of traffic lights)			
Boundary conditions		$s(t_f) = s_f,\ v(t_f) = v_f$ given s_0 and v_0			

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