U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Analysis

2017 Annual Progress Report

Vehicle Technologies Office

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Disclaimer

Acknowledgements

Thank you to the principal investigators and their teams for contributing to this Annual Progress Report. Their hard work and ideas result in the success of the Vehicle Technologies Office and enable important improvements in fuel economy and the efficiency of the transportation system as a whole.

We would also like to acknowledge Energetics for their support in preparing, publishing, and managing the compilation of this report.

Acronyms

AEO	Annual Energy Outlook
AFV	alternative fuel vehicle
ANL	Argonne National Laboratory
ARB	California Air Resources Board
AVCEM	Advanced Vehicle Cost and Energy-use Model
AWARE	Available Water Remaining
BatPaC	Battery Performance and Cost Model
BEAM	Behavior, Energy, Autonomy, and Mobility
BEV	battery electric vehicle
bpd	barrels per day
CAV	connected and automated vehicle
CCS	carbon capture and storage
CF	characterization factor
CHP	combined heat and power
CO2	carbon dioxide
CO2e	carbon dioxide equivalent
DCFC	direct current fast charge
DOE	U.S. Department of Energy
EEMS	Energy Efficient Mobility Systems Program
EERE	Energy Efficiency and Renewable Energy
EIA	Energy Information Administration
EV	electric vehicle
EVI-Pro	Electric Vehicle Infrastructure Projection tool
eVMT	electric vehicle miles traveled
EVSE	electric vehicle supply equipment
FAF	Freight Analysis Framework
FCEV	fuel cell electric vehicle

FCTO	Fuel Cell Technologies Office
FOTW	Fact of the Week
FY	fiscal year
gCO2e	gram CO2 equivalent
GPRA	Government Performance and Results Act
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Transportation
GWh	gigawatt hour
HD	heavy-duty
HDV	heavy-duty vehicle
HEV	hybrid-electric vehicle
HWC	human water consumption
ICEV	internal combustion engine vehicle
kWh	kilowatt hour
L2	level 2 (240 volt) charging
LCA	life cycle analysis
LD	light-duty
MA3T	Market Acceptance of Advanced Automotive Technologies Model
MD	medium-duty
mpg	miles per gallon
mph	miles per hour
MSRP	manufacturer’s suggested retail price
NEAT	Non-Light Duty Energy and GHG Emissions Accounting Tool
NG	natural gas
NGV	natural gas vehicle
NL	nested logit
NREL	National Renewable Energy Laboratory
ORNL	Oak Ridge National Laboratory
PEV	plug-in electric vehicle

PHEV	plug-in hybrid electric vehicle
SMART	Systems & Modeling for Accelerated Research in Transportation
TCO	total cost ownership
TDP	Transportation Data Program
TOU	time-of-use
U.S. DOT	United States Department of Transportation
VMT	vehicle miles traveled
VTO	Vehicle Technologies Office

Executive Summary

During fiscal year 2017 (FY 2017), the U.S. Department of Energy Vehicle Technologies Office (VTO) funded analysis projects supportive of VTO's goals to pursue early stage research in vehicle and mobility system technologies to reduce petroleum dependence, increase energy reliability and security, improve transportation affordability, and promote economic growth. VTO analysis projects result in a foundation of data, analytical models, and applied analyses that provide insights into critical transportation energy problems and assist in research investment prioritization and portfolio planning.

This document presents a brief overview of VTO analysis efforts and progress for projects funded in FY 2017. Each of the progress reports includes project objectives, approach, and highlights of the technical results that were accomplished during the fiscal year.

Table of Contents

List of Figures

List of Tables

Vehicle Technologies Office Overview

Vehicles move our nation. Vehicles transport more than $36 billion worth of goods each day[1] and move people more than 3 trillion vehicle-miles each year[2]. Growing our national economy requires transportation and transportation requires energy. The average U.S. household spends nearly one-fifth of its total family expenditures on transportation[3], making transportation the most expensive spending category after housing. The transportation sector accounts for 70% of U.S. petroleum use. The United States imports 25% of the petroleum consumed – sending more than $10 billon per month[4] overseas for crude oil.

To strengthen national security, enable future economic growth, and increase transportation energy efficiency, the Vehicle Technologies Office (VTO) funds early-stage, high-risk research on innovative vehicle and transportation technologies. VTO leverages the unique capabilities and world-class expertise of the national laboratory system to develop innovations in electrification, advanced combustion engines and fuels, advanced materials, and energy efficient mobility systems.

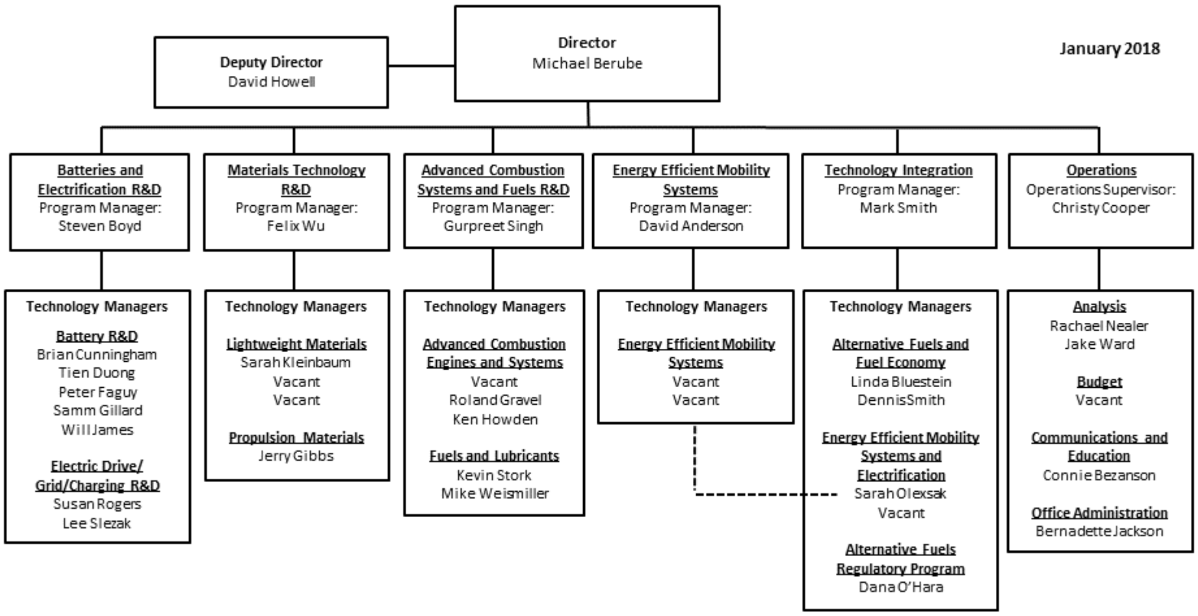
VTO is uniquely positioned to address early-stage challenges due to strategic public-private research partnerships with industry (e.g., U.S. DRIVE, 21st Century Truck Partnership). These partnerships leverage relevant expertise to prevent duplication of effort, focus U.S. Department of Energy (DOE) research on critical R&D barriers, and accelerate progress. VTO focuses on research that industry does not have the technical capability to undertake on its own, usually due to a high degree of scientific or technical uncertainty, or it is too far from market realization to merit industry resources. VTO's research generates knowledge that industry can advance to deploy innovative energy technologies to support affordable, secure, and efficient transportation systems across America.

[1] https://ops.fhwa.dot.gov/publications/fhwahop16083/ch1.htm#t1

[2] https://www.fhwa.dot.gov/policyinformation/statistics/2015/vm1.cfm
[3] https://www.bls.gov/cex/2015/standard/multiyr.pdf

[4] Transportation Energy Data Book Edition 34, ORNL, Table 1.7 and Table 10.3. Overseas includes countries and territories outside the 50 States and the District of Columbia.

Vehicle Technologies Office Organization Chart



Analysis Program Overview

Introduction

VTO invests in research and development of advanced vehicle technologies and energy-efficient mobility systems that will increase America's energy security, economic vitality, and quality of life. The impact of VTO's investments depends on the eventual commercialization of supported technologies. Therefore, maximizing the benefits achieved requires development of a portfolio based on a fundamental understanding of the complex system within which transportation technologies are manufactured, purchased, and used. This system is shaped by the actions and interactions of manufacturers, consumers, markets, infrastructure, and the built environment.

The VTO Analysis Program supports mission-critical technology, economic, and interdisciplinary analyses to assist in prioritizing VTO technology investments and to inform research portfolio planning. These efforts provide essential vehicle and market data, modeling and simulation, and integrated and applied analyses, using the unique capabilities, analytical tools, and expertise resident in the national laboratory system.

Key questions addressed by these data, modeling, and analysis efforts include:

- What vehicle use domains have the greatest potential to provide benefits in efficiency gains, fuel cost savings, economic growth, and protection of human health? In what applications can new technologies make the greatest impact?
- What trends in vehicle miles of travel (VMT), vehicle ownership, fuel and technology choice, infrastructure development, consumer behavior, and other factors are likely to impact the achievement of future benefits?

- As sales of electric vehicles (EVs) grow, what are the infrastructure needs? How will they impact the electricity grid? Will this trend save consumers money and improve human health?
- As demand for freight transportation grows, how can we improve the efficiency of moving the goods we buy?
- How will developments in vehicle connectivity and autonomy impact energy demand? How do we ensure that these developments lead to a safe, efficient, and clean transportation system?
- What will the future look like if we meet all our subprogram targets? What if our subprograms fall short?

Goals

The goals of the VTO Analysis Program are to:

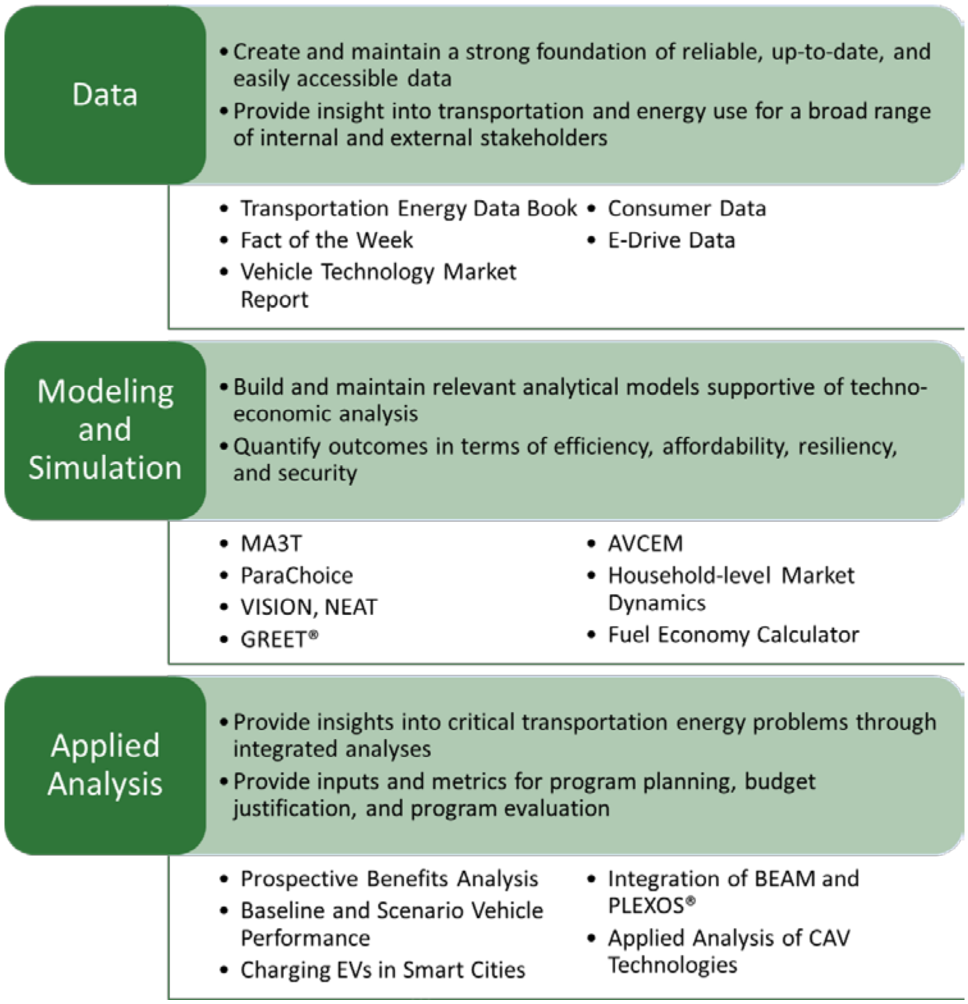
- Assist VTO in prioritizing technology investments and inform research portfolio planning
- Support quantitative assessment of vehicle and mobility technology impacts
- Provide insight into transportation and energy use problems for a broad range of internal and external stakeholders

To achieve these goals, the Analysis Program supports activities with the following three broad objectives:

- Create and maintain a strong foundation of data
- Build, maintain, and exercise relevant analytical models
- Execute insightful integrated analyses that provide greater understanding of critical transportation energy problems.

Program Organization Matrix

The Analysis Program activities are organized within three areas as described above: (1) data, (2) modeling and simulation, and (3) applied analysis. The figure below illustrates the relationship between these three areas, the program goals, and the activities summarized in this report.



For FY 2017, several applied analysis activities within VTO's Systems & Modeling for Accelerated Research in Transportation (SMART) Mobility Consortium were co-funded by the VTO Analysis team and VTO's Energy Efficient Mobility Systems (EEMS) Program. Several of the SMART Mobility project reports appear in both the Analysis FY 2017 Annual Progress Report and the EEMS FY 2017 Annual Progress Report.

I. Transportation Data Program

I.1 Transportation Energy Data Book, Vehicle Technologies Market Report, Fact of the Week

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Start Date: October 1, 2016 End Date: September 30, 2018
Total Project Cost: $503,500 DOE share: $503,500 Non-DOE share: $0

Project Introduction

Transportation analysts and VTO staff require quality current and historical data and information on the transportation sector to inform stakeholders. The Transportation Data Program (TDP) provides a wealth of information, which is used as a DOE resource to improve analyses of the transportation sector, which contribute to program planning, evaluation, and technology research in the public and private sectors. Stakeholders use this data to help move the US towards affordable transportation, reduce our petroleum dependence, and increase our national security.

Objectives

The Transportation Data Project will (1) produce a report including data and information about the new vehicle market and factors that affect the market, (2) produce the text, graphic, and data for a Fact of the Week (FOTW) to be posted on the VTO website each week of the Fiscal Year (FY), and (3) produce a draft of Edition 36 of the *Transportation Energy Data Book*, including updated data and information on the transportation sector, with an emphasis on energy.

Approach

Oak Ridge National Laboratory's (ORNL's) approach for the TDP can be categorized into four stages: discovery, due diligence, approval, and publication (Figure I.1.1). Data are discovered from a myriad of public and private sources, and ORNL provides due diligence to ensure the data are defined and notated correctly. In this stage of the approach, ORNL works with other laboratories (e.g., Argonne National Laboratory (ANL) and the National Energy Renewable Laboratory), government agencies (e.g., Federal Highway Administration), and private companies (e.g., Wards Automotive) to compile and understand the data that are collected, being careful to ensure data are comparable. Explanatory text is written, and tabulations/graphics are generated in Word or Excel. Each FOTW and the tabulations/graphics in the Market Report and Data Book are reviewed and approved by the DOE before final publication. Publication of the FOTW is in the form of website posting on the VTO Transportation Fact of the Week (https://energy.gov/eere/vehicles/transportation-fact-week) web page and programming in the GovDelivery system to be sent to the email subscription list every week, typically on Monday afternoons. The Vehicle Technologies Market Report (http://cta.ornl.gov/vtmarketreport/index.shtml) and the Transportation Energy Data Book (http://cta.ornl.gov/data/index.shtml) is the posting of PDF and Excel files on websites hosted by ORNL. The major topics for the TDP are provided in Table I.1.1.

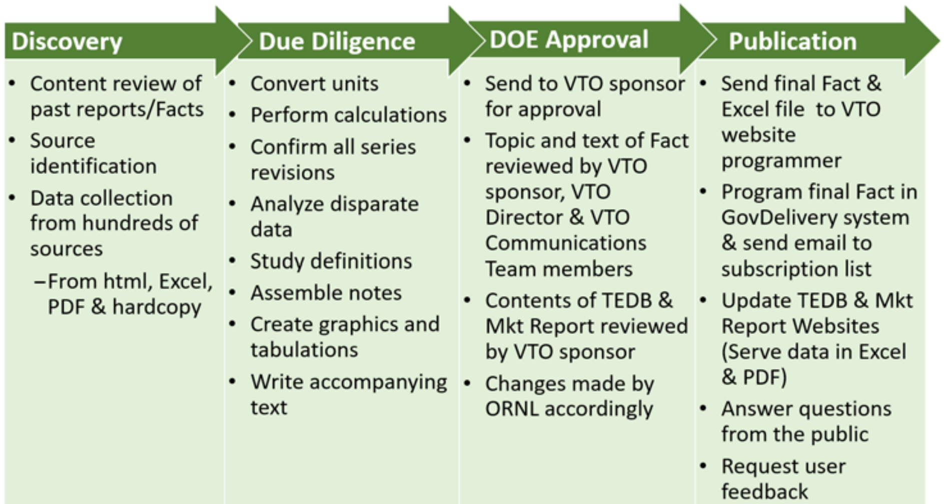

Figure I.1.1 - Approach for the Transportation Data Program at ORNL

Table I.1.1 - Major Topics for the Transportation Data Program at ORNL

Transportation Energy Data Book Topics	Vehicle Technologies Market Report Topics	Fact of the Week Topics
Petroleum	Energy & Economics	All types of transportation topics, focused on highway vehicle data & technologies. Most common themes are: vehicle fuel economy, petroleum use & production, vehicle sales, and traveler behavior.
Energy	Light Vehicles	
Light Vehicles & Characteristics	Heavy Trucks	
Heavy Vehicles & Characteristics	Technologies	
Alternative Fuel & Advanced Technology Vehicles & Characteristics	Policy	
Fleet Vehicles & Characteristics		
Household Vehicles & Characteristics		
Nonhighway Modes		
Transportation & the Economy		
Emissions		
Energy Conversions		

Results

Facts of the Week 945 through 996 were posted on the VTO website during FY 2017 (Table I.1.2). For FY 2017, FOTW content accounted for 168,216 pageviews, or 33% of all VTO website pageviews during the FY. Of those, 151,261 were unique visits, meaning that some visitors (16,955) to FOTW content were repeat visitors. Of all VTO website visits, 52% (140,072) entered the site through a FOTW landing page. Fact 915, *Average Historical Annual Gasoline Pump Price from 1929-2015*, had the highest number of pageviews of any VTO website page – 96,745 or 19% of all website pageviews during the FY.

The weekly email for the FOTW (referred to as a newsletter), began on July 27, 2015, with 50 email subscribers. All subscriptions are voluntary, and an "unsubscribe link" is provided in every email. At of the end of FY 2017, there were 7,756 subscribers to the Transportation FOTW newsletter.

Table I.1.2 - Facts of the Week posted on the Vehicle Technologies Office website in FY 2017

Fact Number	Fact Title	Date Posted on Website
#996	Transportation Accounts for Nearly Three Quarters of Petroleum Consumption	September 25, 2017
#995	Electric Vehicle Charging at Home Typically Draws Less Than Half the Power of an Electric Furnace	September 18, 2017
#994	Electric Vehicle Charging Consumes Less Energy than Water Heating in a Typical Household	September 11, 2017
#993	By Value, Nearly Three-Fourths of Imports from Mexico and More Than Half of Imports from Canada are Transported by Truck	September 4, 2017
#992	Motor Vehicles Are One of the Most Valuable Commodities Shipped in the United States	August 28, 2017
#991	By Mode of Transportation, Freight Tonnage and Freight Value Show Different Trends	August 21, 2017
#990	Comparison of Vehicle Efficiencies Using the Air Conditioner versus Windows Down	August 14, 2017
#989	The Most Common Price Point for Light Vehicles Sold in 2016 was $27,000	August 7, 2017
#988	The Average Price of a New Light Vehicle was Nearly $32,000 in 2016	July 31, 2017
#987	What Do We Pay for in a Gallon of Gasoline?	July 24, 2017
#986	The Price of a Barrel of Crude Oil in 2016 Was the Lowest Since 2003	July 17, 2017
#985	Average Historical Annual Gasoline Pump Price, 1929–2016	July 10, 2017
#984	It is More Efficient to Stop and Restart a Vehicle's Engine than to Idle for as Little as Ten Seconds	July 3, 2017
#983	Proper Tire Pressure Saves Fuel	June 26, 2017

#982	Slow Down to Save Fuel: Fuel Economy Decreases About 14% When Traveling at 70 mph Versus 60 mph	June 19, 2017
#981	Using a Cargo Box on Top of a Vehicle Can Reduce Fuel Economy by 25%	June 12, 2017
#980	Use of Lightweight Materials Has Increased in the Last 20 Years	June 5, 2017
#979	More than One-Third of New Transmissions in 2016 Had a High Number of Gears	May 29, 2017
#978	New Technology Penetration in Light Vehicles	May 22, 2017
#977	Nearly One Quarter of Vehicles Sold in Norway in 2016 were Plug-in Vehicles	May 15, 2017
#976	China has the Highest Number of Sales of Plug-in Vehicles in the World	May 8, 2017
#975	Over Half of All-Electric Vehicle Sales in 2016 Were Large Cars and Standard SUVs	May 1, 2017
#974	Plug-in Vehicle Sales Increased 40% in 2016	April 24, 2017
#973	Truck Stop Electrification Services to Reduce Idling Are Available in 35 States	April 17, 2017
#972	Thirteen Percent of Vehicles Worldwide Are Produced in the United States	April 10, 2017
#971	Production and Manufacturing Comprise One-Third of Motor Vehicles Jobs	April 3, 2017
#970	Eleven Percent of Motor Vehicles Jobs Focus on Alternative Fuel and Advanced Technology Vehicles	March 27, 2017
#969	New Vehicle Fuel Economy Has Improved 33% From 1980 to 2016	March 20, 2017
#968	All-electric Vehicles Have the Lowest Estimated Annual Fuel Cost	March 13, 2017
#967	$500 to $3,850: Wide Range for Model Year 2017 Estimated Annual Fuel Costs	March 6, 2017
#966	Production of Petroleum in the United States was at an All-time High in 2015	February 27, 2017
#965	The United States Produced More Petroleum than Any Other Country in 2015	February 20, 2017
#964	Motor Gasoline Is Most Common Petroleum Product from U.S. Refineries	February 13, 2017
#963	Share of Petroleum Product Output from Refineries Varies by World Region	February 6, 2017
#962	Vehicles per Capita: Other Regions/Countries Compared to the United States	January 30, 2017
#961	Alternative Fuel Corridors Established by the Federal Highway Administration	January 23, 2017
#960	Electricity and Compressed Natural Gas Fuels had the Lowest Price Variability Over the Past 16 Years	January 16, 2017

#959	Record Light Vehicle Sales in 2016	January 9, 2017
#958	Sixty-three Percent of All Housing Units have a Garage or Carport	January 2, 2017
#957	List of the Top Ten Most Fuel Efficient Light Vehicles, Model Year 2017	December 26, 2016
#956	Thirty-four Percent of Light Vehicles Produced in Model Year 2016 were Sport Utility Vehicles	December 19, 2016
#955	New Light Vehicle Fuel Economy at an All-Time High	December 12, 2016
#954	Gasoline Taxes in the United States Were Below 20% of the Total Price in 2015	December 5, 2016
#953	On-road Transportation Consumes More than 80% of all Transportation Energy	November 28, 2016
#952	NHTSA and EPA Finalized Medium and Heavy Truck Fuel Efficiency and Greenhouse Gas Standards through Model Year 2027	November 21, 2016
#951	Medium and Heavy Trucks Account for About a Quarter of Highway Vehicle Fuel Use	November 14, 2016
#950	Well-to-Wheel Emissions from a Typical EV by State, 2015	November 7, 2016
#949	Reduced CO_2 Emissions in the Electric Power Sector Will Benefit the Transportation Sector as Electrification Grows	October 31, 2016
#948	Carbon Dioxide Emissions from Transportation Exceeded those from the Electric Power Sector for the First Time in 38 Years	October 24, 2016
#947	Over Half a Million Plug-in Vehicles Have Been Sold in the United States as of September 2016	October 17, 2016
#946	Driving Alone in a Private Vehicle is the Most Common Means of Transportation to Work	October 10, 2016
#945	Vehicle Miles of Travel Has Reached New Highs	October 3, 2016

The Vehicle Technologies Market Report was published on-line on May 25, 2017 providing PDF files and Excel spreadsheets of the tables and figures in the report (Figure I.1.2). The report has 160 figures and 46 tables of data and information on the new vehicle market and vehicle technologies. The draft of the Transportation Energy Data Book: Edition 36 was provided to the VTO for comment on September 29, 2017. After reviews, changes, and approvals were completed, the report was posted on the website in December 2017 (Figure I.1.3). There are 212 tables and 52 figures of data and information on the transportation sector, with an emphasis on energy.

Figure I.1.2 - Vehicle Technologies Market Report website home page

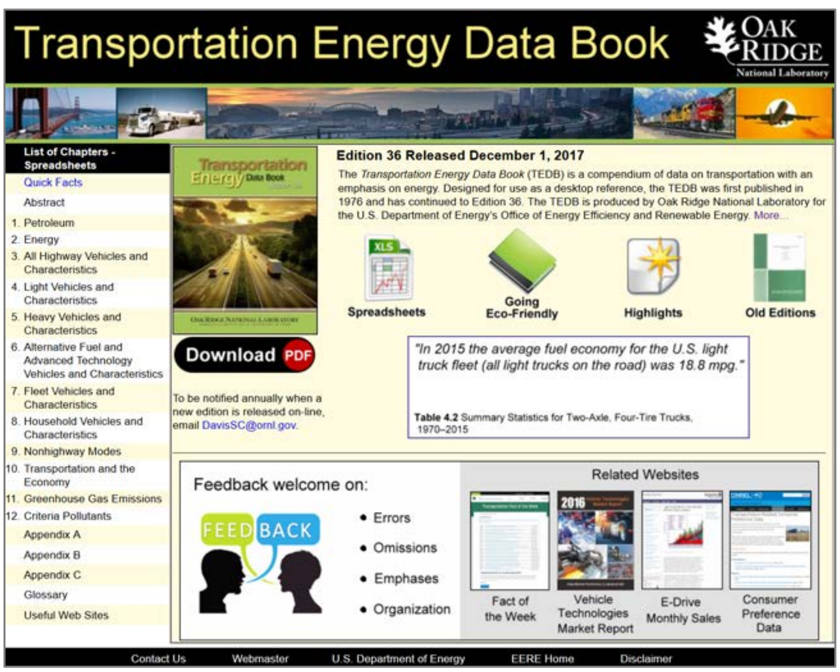

Figure I.1.3 - Transportation Energy Data Book website home page

The Transportation Energy Data Book website had approximately 89,000 visitor sessions in FY 2017, and the Vehicle Technologies Market Report website had nearly 42,000 visitor sessions. Google Scholar reports about 3,150 citations for the Transportation Energy Data Book, and 114 citations for the Vehicle Technologies Market Report.

Data collected in the TDP also provided input data to other VTO programs and other Agency's models, such as: MA3T, GREET®, ADOPT, Parachoice, prospective program benefits analysis, the Energy Information Administration's (EIA's) National Energy Modeling System, and Environmental Protection Agency MOVES model.

Conclusions

Successful publication of the TDP in the form of weekly, monthly, and annual milestones delivered on-time and within budget with improvements over time, leads to analyses that support program planning and evaluation and technology research to address transportation efficiency and cost-effectiveness, which will help meet the research and development priorities of the DOE of energy dominance.

Key Publications

Davis, S.C., S.E. Williams, R.G. Boundy, and S. A. Moore (2017), 2016 *Vehicle Technologies' Market Report*, ORNL/TM-2017/238, Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Davis, S.C., S.W. Diegel and R.G. Boundy (2017), *Transportation Energy Data Book: Edition 36*, ORNL/TM-2017/513, Oak Ridge National Laboratory, Oak Ridge, Tennessee. [Draft completed in FY 2017. Published in final form in FY 2018.]

I.2 Consumer Data Program

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Start Date: October 1, 2016 End Date: September 30, 2018
Total Project Cost: $212,273 DOE share: $212,273 Non-DOE share: $0

Project Introduction

The Consumer Data Program supports VTO goals by providing VTO staff and other stakeholders with insights into consumer sentiments on technologies that make up the VTO portfolio, in support of its mission of researching, developing, and implementing technologies to improve energy security, enhance mobility flexibility, and reduce transportation costs.

The effort is built upon feedback from end-users and new vehicle technology early adopters and is enhanced with published consumer survey data and additional data from third-party survey providers that gather data for specific consumer sentiments. The capability is flexible and able to identify trends and then react to quickly changing marketplace dynamics or shifting research focus areas and needs. The project coordinates with external stakeholders with broad market knowledge and expertise to determine areas where a deeper understanding of consumer sentiments is most valuable. The project works to understand the relationship between survey responses and actual behavior to properly contextualize response data and improve future survey efforts.

Consumer sentiment data are disseminated through formalized published reports, as well as through focused releases that support the VTO Quarterly Analysis Review, the VTO FOTW effort, and other opportunities to make data available to interested parties within the research community and the public. Where interests are aligned, the project coordinates with other DOE programs, including Clean Cities, the State and Alternative Fuel Provider Program, and the Federal Energy Management Program.

Objectives

The objective of the Consumer Data Program is to provide feedback to VTO on projects and priorities and to support analysis and decision making regarding their research portfolio. The program provides data on existing consumer behaviors as well as consumer awareness of, understanding of, and preferences for new technologies, and how these new technologies may affect their energy use habits. Understanding these trends and preferences will help DOE stakeholders increase energy security and economic growth through innovation and technology improvements that reduce petroleum imports and improve energy affordability.

Approach

A primary focus of the program is the understanding of market and consumer values, development of consumer question sets, analysis of consumer data and study results, and publication of findings. The surveys are conducted by a subcontractor, which uses a mechanism designed to represent the general U.S. population and adds these vehicle technology questions to their established outreach. Studies are developed with input from a broad working group of VTO Analysis Program experts, partner agencies, DOE national laboratories, academia, and private researchers.

A sample of previous consumer sentiment topic areas include the following:

- Plug-in electric vehicle (PEV) awareness and exposure
- All-electric vehicle battery driving range requirements
- Willingness to pay for fuel economy and PEVs
- Fuel economy perceptions
- Automated vehicle awareness, interest, and expectations.

Beyond original studies, the Consumer Data Program tracks and pulls from existing consumer survey data to inform study development and understand gaps in publicly available data sets.

The effort makes results available through formal reports and targeted releases of ad hoc study data. The principal product of the program since 2015 has been *The Barriers to Acceptance of Plug-in Electric Vehicles* report, which is now in a third edition detailing annual trends in PEV sentiments.

Study results support VTO Analysis Program efforts including the Transportation Energy Data Book, Vehicle Technologies Market Report, FOTW, and the VTO Quarterly Analysis Review amongst others.

The program understands that actual consumer behavior data (revealed preferences) is preferable where available, but the stated preference data captured and shared by the effort provides a supplemental source to validate other data and a new resource when no data are available.

Results

The Barriers to Acceptance of Plug-in Electric Vehicles: 2017 Update reports detailed findings of a February 2017 study investigating consumer views of PEVs. The study is the third in a series of annual studies designed to define and track evolving consumer views of PEVs. The results provide a national benchmark for these views as PEVs develop in the marketplace.

The high-level trends in Table I.2.1 show PEV views have been relatively stable since the questions were first asked in February 2015. However, awareness of PEV charging stations has increased, and a consistent finding of the studies has been that those respondents that are aware of PEV charging stations are more likely to state they are expecting to consider purchasing a PEV (Figure I.2.1).

Table I.2.1 - Plug-in Electric Vehicle Views Summary

	Topic Area	Feb 2015	Feb 2016	Feb 2017
PEV Awareness	Able to name a specific PEV	48%	46%	46%
	Aware of PEV tax incentives	NA	33%	23%
Barriers to PEV Acceptance	Able to plug in at home	53%	49%	54%
	300 miles sufficient all-electric vehicle range	56%	46%	47%
	Unaware of PEV charging stations	79%	76%	70%
	Willing to pay extra for a PEV	51%	49%	47%

PEV Acceptance	Expect to consider a PEV (Exepct to buy)	20-24% (2%)	19-23% (3-4%)	21-24% (2-3%)

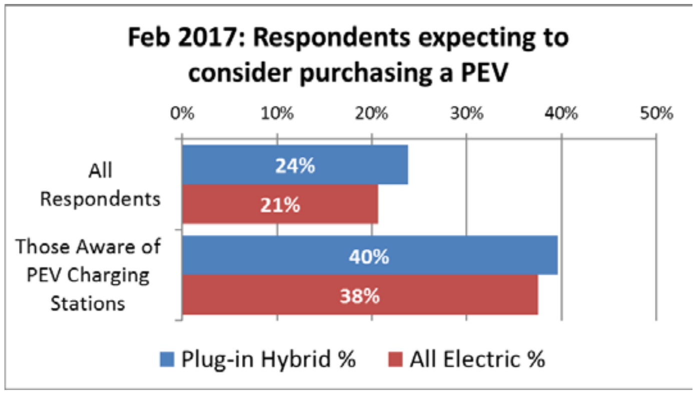

Figure I.2.1 - Considering PEVs and PEV charging station awareness

In addition to the PEV views study, the Consumer Data Program conducts ad hoc studies in support of other VTO Analysis Program efforts, and has maintained trends of some key consumer views on transportation energy usage. Figure I.2.2 presents an example showing that the relative importance of fuel economy has trended similarly to gasoline prices over time.

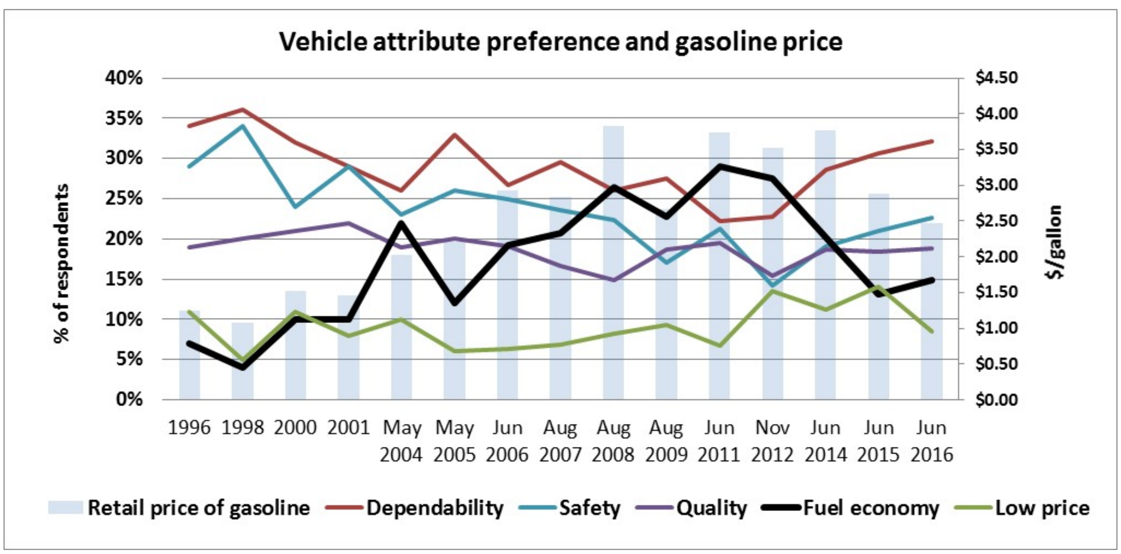

Figure I.2.2 - Relative importance of fuel economy and gasoline price

The Consumer Data Program completed an automated vehicle study in 2017 designed to capture data on how automated vehicle usage may affect VMT. The study seeks to learn from consumers about how they expect to use the new technology and what respondent demographic segments may be most or least likely to use automated vehicles.

In 2017 the Consumer Data Program created a website to more easily share historical reports and ad hoc data presentations as they are published.

Conclusions

The Consumer Data Program provides VTO a capability to track and investigate high-level consumer sentiments and provides a voice of the consumer to contextualize and prioritize research. The program provides VTO a mechanism for capturing consumer preferences affecting energy usage that is flexible as research direction evolves. The results of this project will help inform key stakeholders in order to advance DOE and VTO missions.

Key Publications

National Renewable Energy Laboratory (2017). *Transportation-Related Consumer Preference Data*. Accessed January 19, 2018: https://www.nrel.gov/transportation/consumer-data.html

Singer, M. 2017a. *The Barriers to Acceptance of Plug-in Electric Vehicles: 2017 Update*. NREL/TP-5400-70371. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy18osti/70371.pdf

Singer, M. 2017b. *Consumer Views: Fuel Economy, Plug-in Electric Vehicle Battery Range, and Willingness to Pay for Vehicle Technology*. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy17osti/68201.pdf

Singer, M. 2017c. *Consumer Views: Importance of Fuel Economy*. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy17osti/68200.pdf

I.3 E-Drive Data

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Start Date: October 1, 2016 End Date: September, 30 2017
Total Project Cost: $55,000 DOE share: $55,000 Non-DOE share: $0

Project Introduction

E-drive vehicle technologies include hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). VTO has supported analysis of light-duty (LD) market trends in order to assess potential benefits of VTO supported technologies and to evaluate program activities. A major challenge is the lack of readily available historical sales and government action (both financial and non-financial) in the United States and other markets, as well as limited understanding of advanced vehicle sales trends and consumer choice geospatially in the United States. Moreover, regional E-drive vehicle purchase trends need to be systematically examined to provide support and guidance for national impacts analyses (e.g., potential energy and emission reduction) and infrastructure needs. In addition, information on the total cost of ownership (TCO) of E-drive vehicle technologies and how they compare with conventional counterparts need to be collected and summarized for use in applied analyses and macroeconomic accounting tools to help VTO better understand the levelized cost for consumers (e.g., initial cost, operation cost). These tools support assessment of the affordability of transportation.

Objectives

The objective is to collect and provide readily useable sales and ownership cost data, analyze regional sales patterns to improve market modeling of the electric-drive vehicle ecosystem, and support other DOE programs. There are three sub-tasks: (1) track global E-drive Sales, (2) examine U.S. regional sales patterns, and (3) collect vehicle ownership cost. External and internal stakeholders can use this information to make better decisions as they develop technology and mobility systems that will improve affordability of transportation, decrease our dependence on petroleum, and foster innovation to help grow the economy.

Approach

Task 1: Track Global E-drive Vehicle Sales

ANL collected global monthly E-drive sales data by make/model and related pricing information for major markets (the United States, Western Europe, China and Japan) from several sources, including the European Automotive Industry Newsletter. ANL collaborates with Tsinghua University, Beijing, China to collect both sales and policy information from China and Japan. Sales data for the China market includes both LD and buses. The U.S. sales by make and model is updated monthly on the ANL website (http://www.anl.gov/energy-systems/project/light-duty-electric-drive-vehicles-monthly-sales-updates) and a monthly market report is released to public subscribers. ANL also summarizes the sales of other regions (China, Europe, and Japan), and provides interpretation to VTO and other DOE offices through reports and presentations as needed. ANL provides aggregated sales information and market trends to be documented in the Transportation Energy Data Book, the Vehicle Technologies Market Report, and the VTO FOTW.

Task 2: Examine U.S. Regional Sales Patterns
R.L. Polk data on PHEV/BEV vehicle registration by city and state, provided by the National Renewable Energy Laboratory (NREL), is used to (a) report current regional market status for VTO, and (b) conduct scientific analyses of market characterization to determine locations of PEV sales. Under (a), summaries of sales by states and selected cities/regions (regions that have high PHEV/BEV sales) are constructed to provide information sources for VTO. Under (b) ANL examined the impact of state incentives, infrastructure development, DOE/VTO programs, and geographic variations on regional PEV adoption.

Task 3: Collect Resale Values and TCO of E-drive Vehicle and Summarize Depreciation Rates
ANL collected true market value and five-year TCO from Edmunds for selected HEV, PHEV, BEV models (volume leaders in each category), and for selected conventional counterparts. ANL conducted statistical analyses to compare the resale and adjusted retention rate across regions and time (years) for different market segments and vehicle size classes. ARR is calculated using the following equation:

$$\text{Adjusted Retention Rate}_i = \frac{\text{New Car Price} - \text{Depreciation Value Till Year } i}{\text{New Car Price} - \text{Tax Credits}}$$

Results

Task 1: ANL tracked U.S. E-drive vehicle monthly sales by make and model, and released monthly reports to over a hundred of subscribers. Subscribers are diverse and include automotive manufacturers, Federal and State agencies, universities, and research institutions. Reports summarize monthly and annual sales trends and correlation with other economic factors, such as gross domestic product, gasoline price, and unemployment rate. ANL also published selected data on the [ANL website](http://www.anl.gov/energy-systems/project/light-duty-electric-drive-vehicles-monthly-sales-updates) monthly (http://www.anl.gov/energy-systems/project/light-duty-electric-drive-vehicles-monthly-sales-updates). ANL's E-drive sales data has supported DOE Office of Energy Efficiency and Renewable Energy (EERE) programs and activities such as eGallon, Vehicle Market Report, and EERE ***transportation FOTW. Figure I.3.1 shows annual total BEV and PHEV sales. Figure I.3.2 shows cumulative sales of all PEVs and top selling models.

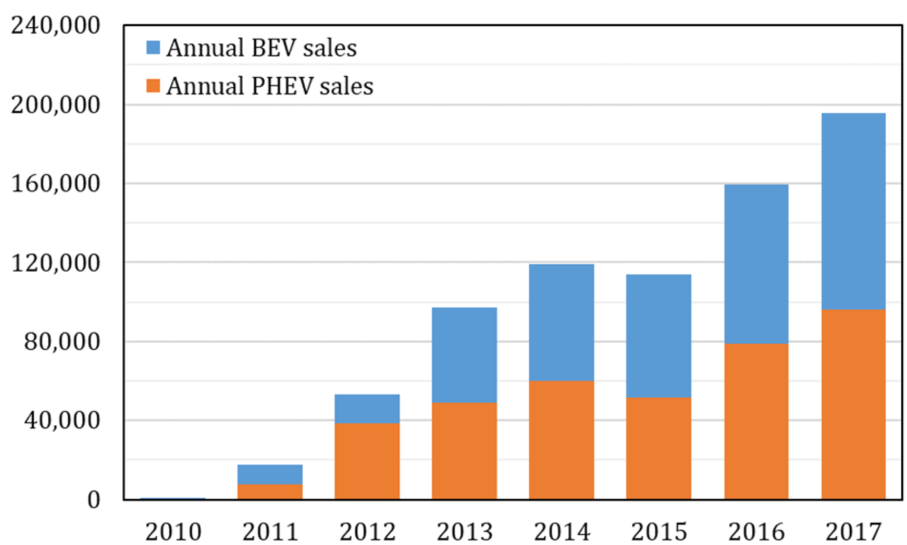

Figure I.3.1 - PEV annual sales in the United States

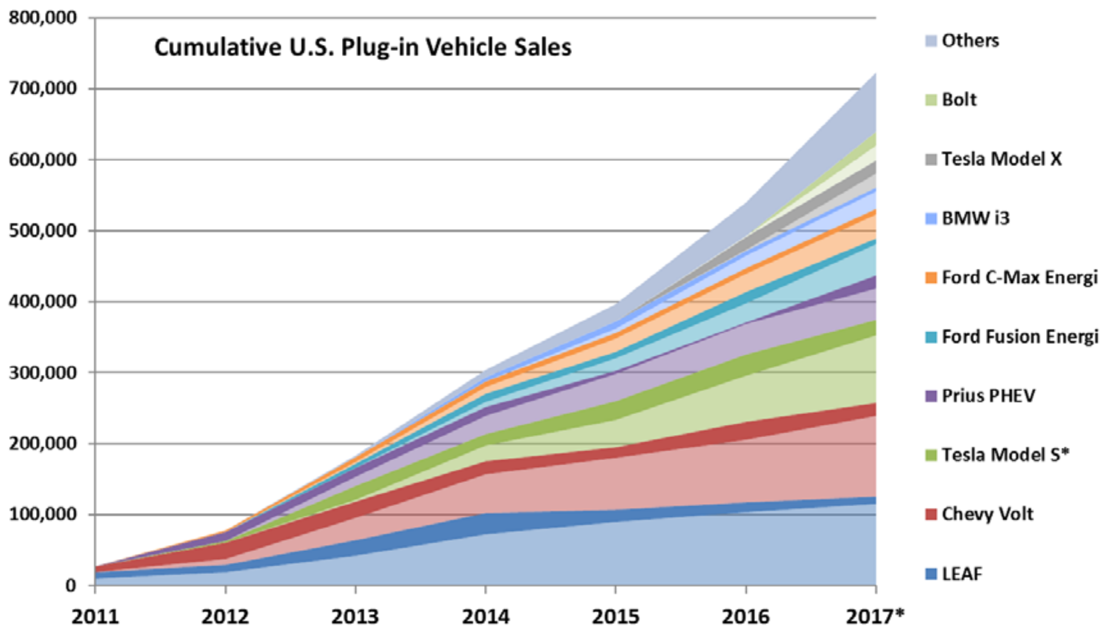

Figure I.3.2 - Cumulative U.S. PEV sales

Task 2: Regional PEV analysis shows that varying sets of variables are significantly correlated with each PEV market segment (mass, medium, luxury) at the county level. Based on statistical analysis conducted using 2014 and 2015 PEV registration at the county level, the following correlations were identified.

- Extreme temperatures were particularly strongly correlated to sales for the total market and for the mass-market BEVs (manufacturer's suggested retail price (MSRP) <$40,000) and negative in sign
- State and federal monetized benefits were twice as important for BEVs as for PHEVs as evidenced by the magnitude of the correlation coefficient
- Level 2 (L2, 240 volt) public charging availability shows statistically significant positive impacts in the mass market (MSRP <$40,000) and total PHEV markets, but not in BEV markets
- Workplace charging shows a positive but lower correlation for BEVs than for PHEVs
- PEV Readiness Grants had consistent positive and generally significant impacts in all PHEV market segments, as well as mass-market and total BEVs
- HOV lane subsidies appear to be highly correlated with sales in the mass market
- Income has statistically significant positive impacts in every market segment, dominating the education effect
- Fuel Cost: Interestingly, gasoline prices are negatively correlated to luxury BEV sales (i.e., MSRP>$60,000), luxury PHEVs, and mid-market PHEVs (i.e., $40,000<MSRP<$60,000), but not mass-markets or total markets (includes mass market, mid-market and luxury market)
- Longer Work Travel Time significantly decreases luxury BEV and mid-market PHEV market adoption, but not mass markets.

Task 3: Statistical analysis based on true market value and TCO data collected from Edmunds in December 2016 shows BEVs have a wide range of three-year value retention rates. Tesla models outperform others. Figure I.3.3 shows the cumulative distribution of three-year adjusted value retention rate of selected vehicle models and types.

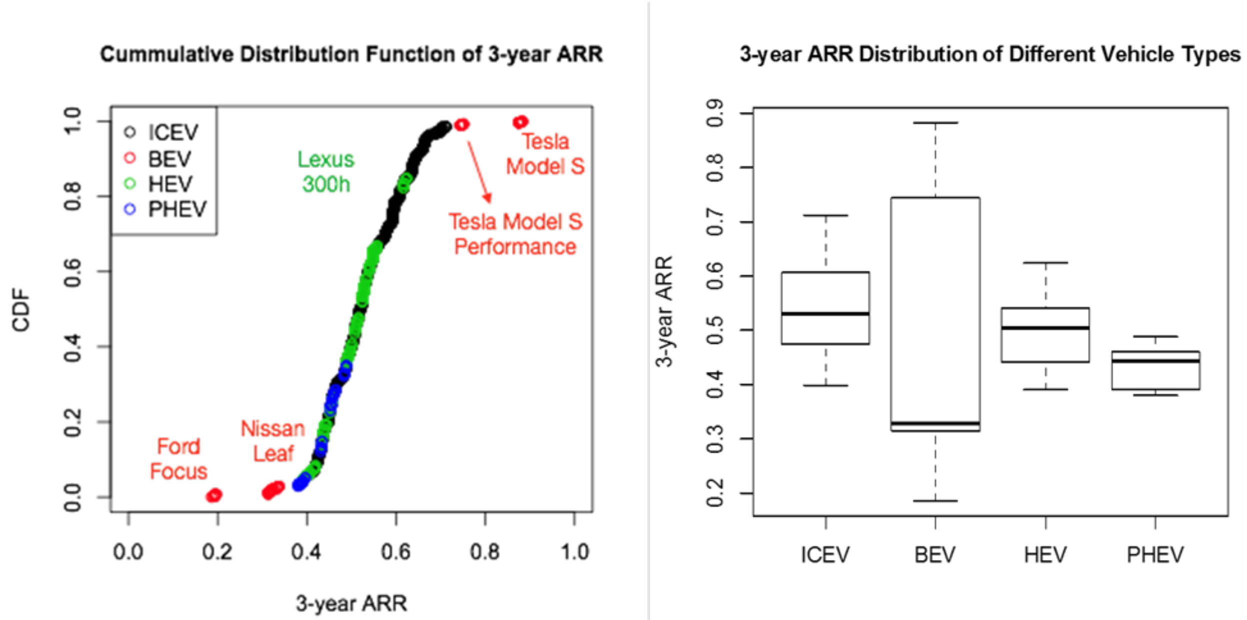

Figure I.3.3 - Cumulative distribution function of three-year adjusted retention rate of selected models and types

Conclusions

Task 1: PEV sales have been increasing in the United States since the first introduction in December 2010. PEV accounts for about 1% of all light-duty vehicle (LDV) sales monthly. China became the leading PEV market in 2015, and kept the position in 2016 with over 300K PEVs sold in 2016.

Task 2: Statistical analysis shows that negative effects of extreme temperature (both warm and hot) were particularly strong for the total market and for the mass-market BEVs (i.e., MSRP <$40K).

Task 3: BEVs have a wide range of three-year value retention rates compared to other vehicle powertrain types (e.g., PHEV, HEV, internal combustion engine vehicles (ICEV)). Tesla models outperform others.

Key Publications

Y. Zhou, D. Santini, K. Vazquez, and M. Rood. “Contributing factors in plug-in electric vehicle adoption in the United States: A Metro/County level approach.” *Proceedings of 96th Transportation Research Board Annual Meeting*, Washington, D.C., Jan. 2017.

Z.M. Guo Y. Zhou and R. Campbell, “Residual Value Analysis of Plug-in Vehicles in the U.S.,” *Proceedings of 97th Transportation Research Board Annual Meeting*, Washington, D.C., Jan. 2018.

II. Modeling and Simulation

II.1 Market Acceptance of Advanced Automotive Technologies

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Start Date: October 1, 2016 End Date: September 30, 2018
Total Project Cost: $1,150,000 DOE share: $1,150,000 Non-DOE share: $0

Project Introduction

Modeling market acceptance of new technology is important to the DOE mission and to its stakeholders to understand and quantify the future value of research and development. Technology impacts (e.g., energy consumption, consumer costs, energy security) are often used to justify and prioritize R&D investments in advanced vehicle technologies. However, consumers may see technologies differently than engineers, scientists and economists. Meanwhile, suppliers seek less risk, more market certainty, and good public image, in addition to profits. This presents challenges in understanding and modeling supplier behavior (e.g., product provision and pricing decisions) and the resulting consumer acceptance of technologies.

To alleviate these challenges, the MA3T model (Market Acceptance of Advanced Automotive Technologies) was developed to simulate the market penetration and dynamics in transition scenarios toward energy efficient vehicle and mobility technologies in the highway sector. The key output of the model is annual sales share of a vehicle or mobility technology (e.g., 42-volt micro hybrid, 200-mile BEV, or autonomous shared mobility). Inputs of the model include consumer segmentation and attributes, technology cost and performance, infrastructure availability and prices, and government incentives. All these inputs can be easily changed, and the operation of the model only requires installation of MS Excel.

The MA3T model was originally developed to focus on fuel choices and was later adapted and upgraded to (1) MA3T-CN that simulates PEV market penetrations in China, (2) MA3T-Global that estimates transportation energy transitions in different regions and countries around the world, and (3) MA3T-MobilityChoice that simulates market penetrations and synergies of electrification, automation, and shard mobility. Some of the work is funded by international organizations and the private sector. Currently, published applications of the model cover the topics of (1) market-driven compliance of the fuel economy standards, (2) program benefit estimates for multiple DOE program offices, (3) biogas electricity incentives for PEVs, (4) PEV market penetration sensitivity, (5) market effect of vehicle automation on electrification, and (6) impact of dynamic wireless charging on PEV sales.

Objectives

The objectives of the MA3T project are to (1) develop a user-friendly, useful, and credible simulation tool in support of techno-economic analysis with respect to energy-relevant vehicle technologies, (2) close key knowledge gaps in fundamental issues for reaching objective 1 above (e.g., how to quantify range anxiety cost), (3) advance discussions of vehicle technologies through publications, and (4) use the model as a coherent intellectual platform to collect industry feedback and engage stakeholders.

Approach

The core of the MA3T model is based on the nested multinomial logit theory, the immediate output from which is the purchase probability of each technology choice by each consumer segment. These probabilities are then translated into vehicle sales by technology, vehicle population, energy consumption, and emissions. These outputs are also used as feedbacks to dynamically affect the conditions and purchase probabilities of the next time step. For example, greater sales lead to more vehicle makes and models and further accelerate market penetration. Inputs of the model include consumer segmentation and attributes, technology cost and performance, infrastructure availability and prices, and government incentives.

The original MA3T model was focused on choice of fuel types (e.g., gasoline conventional vehicles vs HEV vs. PEVs). One major component of the project is to adopt existing or develop new methods for quantifying assumptions and show their impacts on market acceptance (sales and population), energy consumption, and the economy. Assumptions that can be quantified include but are not limited to: (1) Mobility – what if shared mobility eliminates first/last-mile inconvenience? (2) Consumer – what if consumers demand a 3-year payback? (3) Technology – what if batteries cost $80/kWh by 2030 and what if vehicle automation increases travel demand? and (4) Infrastructure – what if fast-charging is strategically offered?

One major expansion during the last year is the expansion to MA3T-MobilityChoice for considering automated and shared mobility technologies. Figure II.1.1 shows the current choice structure of the MA3T-MobilityChoice model, which is designed to address several issues: personal vehicle ownership vs shared mobility, fuel type competition, human-driven or automated vehicles, and the intertwined dynamics of these elements. MA3T-MobilityChoice is jointly sponsored by the DOE's SMART Mobility initiative and will be used to improve the understanding of energy impacts of electrified, automated, and shared mobility technologies.

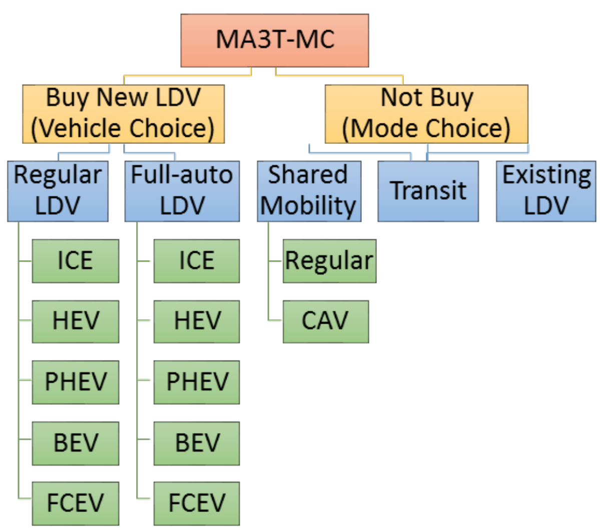


Figure II.1.1 - MA3T-MC: new choice structure to cover vehicle automation, sharing, and fuel types

The project team makes use of existing relevant consumer surveys to better represent consumer behavior. These relevant surveys include National Household Travel Survey, WholeTraveler Survey, Seattle Global Positioning System (GPS) travel data, Advanced PEV Travel and Charging Behavior Survey. In addition, the project team actively explored collaborations with industry partners to see how the MA3T model can benefit industry stakeholders; relevant research topics include the "insurance" value of vehicle features, automation and electrification, and China new energy vehicles. To leverage existing national lab capabilities, the MA3T model has been linked with existing models, such as Autonomie, GREET®, and VISION, and more model collaborations are being sought.

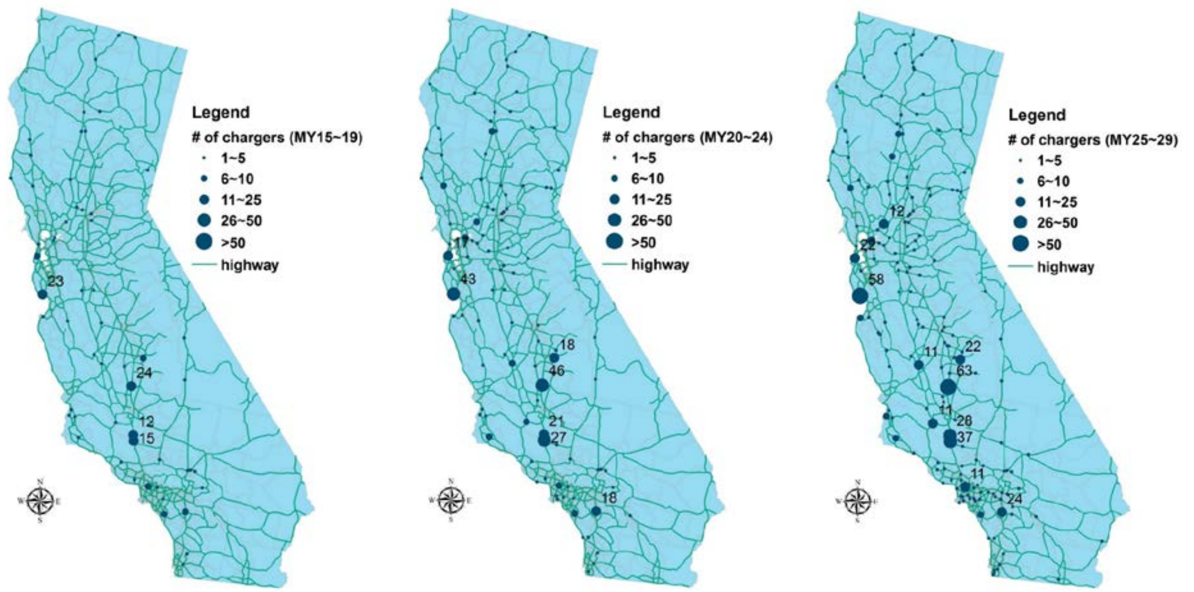
In addition, the team updated the MA3T structure and data to better reflect changes in transportation energy market assumptions. For example, we changed the PHEV technology groups from 10, 20, and 40 miles of all electric range (e-range) to two groups of 25 and 50 miles of e-range. This effort reflects the trend in increasing PHEV range in the vehicle market. In addition, we updated vehicle cost information, fuel economy, and infrastructure based on the new Autonomie simulation from the DOE Baseline and Scenario analysis. We also updated the fuel cost to reflect the EIA's Annual Energy Outlook (AEO) 2017 projection.

Results

Two studies conducted in FY 2017 are highlighted with their major findings described below.

The first study, published in Transportation Research Part E, develops a mathematical model to evaluate where and when charging stations need to be opened, and how many chargers are required for each station, in order to meet growing BEV inter-city demand. Different from prior approaches, queuing theories are integrated into the model to better simulate the randomness in charging operations (random arrivals, departures, and service time). Thanks to the efficient genetic algorithm applied in this study, the model is capable of solving large-scale real-world problems with high resolution on demand nodes (both metropolitan areas and rural towns), complex transportation networks (e.g., the entire California highway network), and multi-year planning requirements. We apply the model to a case study in California with a 15-year planning horizon. This study shows that investment in inter-city charging infrastructure is vital to alleviating range anxiety. The study also finds that planning decisions depend on many factors, such as the design level of service and vehicle range.

Figure II.1.2 shows the charging infrastructure layouts over time for the baseline case. In the figure, locations of circles represent the geographic distributions of charging stations, and the size of each circle indicates the station size in terms of number of chargers. This shows that the charging infrastructure is expanding over time as the BEV inter-city travel demand grows. At stage 1, 56 stations with 226 chargers are opened. At stage 3, the total number of stations and chargers increases to 176 stations and 618 chargers, respectively. The trip coverage (satisfied trips/all trips) remains at high levels in all stages (>99%), as the range limitation cost for each trip is set at a high of $50 per trip. Expanding charging infrastructure is an appealing strategy for all demand levels. For all cases, charging stations are mainly clustered along highways between the San Francisco Bay area and Los Angeles, which are the major traffic demand centers.



- 56 stations / 226 chargers
- Trip coverage: 99.2%

A. Stage 1 (2015–2019)

- 104 stations / 423 chargers
- Trip coverage: 99.8%

B. Stage 2 (2020–2024)

- 176 stations / 618 chargers
- Trip coverage: 99.8%

C. Stage 3 (2025–2029)

Figure II.1.2 - Layouts of charging stations

The second study relates to the development of the MA3T-MC model that integrates all fuel technologies, autonomous technologies, and the sharing economy into one vehicle market modeling framework. This framework will help to quantify the relative effect – that is, to what extent and in what directions, vehicle automation will affect the market penetration of efficient and clean fuel vehicles in competing with gasoline vehicles. It was found that automation makes BEVs more competitive. We found that automation could provide a 30% reduction in per-mile energy use, which is equivalent to an extension of the driving range by 1/0.7-1= 43%, without the extra capital cost to increase the battery capacity. As shown in Figure II.1.3, for a frequent driver at 21,208 annual miles, extending the driving range of a 100-mile BEV to 143 miles makes the BEV range-feasible for 97% of days (up from 87% with a BEV human-driven vehicle). Assuming $50/day of penalty for each day the BEV is not range-feasible due to long distance driving, the automation-enabled range extension is worth $1,825/year to the consumer. This is a significant value. However, consumer heterogeneity must be considered. Some consumers with certain driving patterns may not benefit much from automation and range extension. As also shown in Figure II.1.3, consumers in segment #4 drive below 50 miles per day most of the time. For this segment, the 43% range extension does not increase the range-feasible days and thus is of little value to this consumer.

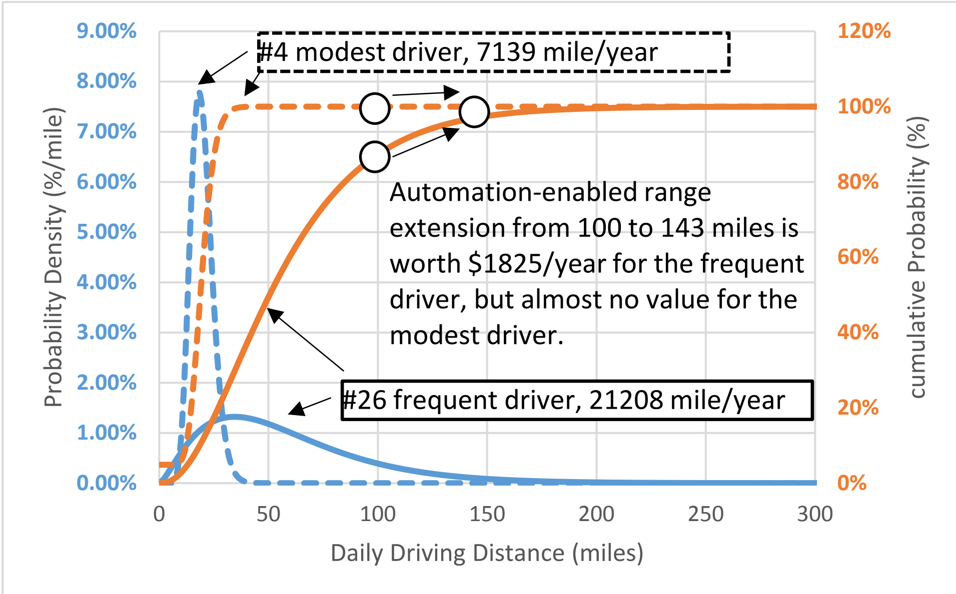


Figure II.1.3 - Value of automation-enabled range extension, 2-driver illustration.

Conclusions

In FY 2017, we have improved the MA3T model to have more capabilities and completed more case studies. We updated the model to cover the charging availability-opportunity linkage, and the information is important to translate the impacts of public charging infrastructure development on the future PEV market share. This new update has been applied to the SMART Mobility Advanced Fueling Infrastructure task 1. Furthermore, we added additional renewable fuel credit information into the MA3T model, and this new feature was applied to investigate the biogas PEV credit with one published technical report and one conference paper. In addition, the MA3T model was integrated with the Monte-Carlo simulation feature to investigate PHEV market uncertainty. Fuel efficiency cost curves were also integrated into the MA3T model, and the new data was used to evaluate incorporation of technologies to meet fuel economy goals. We have also updated the MA3T data (e.g., cost and fuel economy data with the DOE Baseline and Scenario Analysis study) and have been working on the development of the MA3T-MC model. The MA3T model is also getting more international attention.

During FY 2017, the project team published nine peer-reviewed journal papers, and five technical reports. Several manuscripts are currently under review for journal publication.

Despite a productive year, challenges remain. The project team is working on integrating the quantification of travel time recovery, safety benefits, and possibly stress reduction benefits from vehicle automation and shared mobility (e.g., assuming shared vehicle drivers are overall better drivers) and toward a full functional MA3T-MC model in support of urgent analytical needs by the SMART Mobility initiative, and in general by the VTO Analysis office.

Key Publications

All FY 2017 and past-year publications can be found at TEEM.ornl.gov. Some selected papers are listed below:

Xie, Fei, and Zhenhong Lin. 2017. "Market-driven automotive industry compliance with fuel economy and greenhouse gas standards: Analysis based on consumer choice." *Energy Policy* 108:299-311. doi: https://doi.org/10.1016/j.enpol.2017.05.060.

Xie, Fei, Zhenhong Lin, and Rachael Nealer. 2017. "Performance, Cost, and Market Share of Conventional Vehicle Efficiency Technologies?" *Transportation Research Record: Journal of the Transportation Research Board* 2628:67-77. doi: 10.3141/2628-08.

Liu, Changzheng, and Zhenhong Lin. 2017. "How uncertain is the future of electric vehicle market: Results from Monte Carlo simulations using a nested logit model." *International Journal of Sustainable Transportation* 11 (4):237-247. doi: 10.1080/15568318.2016.1248583.

Podkaminer, Kara, Fei Xie, and Zhenhong Lin. 2017. Analyzing the impacts of a biogas-to-electricity purchase incentive on electric vehicle deployment with the MA3T vehicle choice model. Oak Ridge National Laboratory.

II.2 ParaChoice Model

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Start Date: October 1, 2013 End Date: Project continuation determined annually
Total Project Cost: $930,000 DOE share: $930,000 Non-DOE share: $0

Project Introduction

ParaChoice supports the VTO mission using early-stage research to help in the development of technology that will improve affordability of transportation, while encouraging innovation and reducing dependence on petroleum. Analysis with the ParaChoice model addresses three barriers from the VTO Multi-Year Program Plan: availability of alternative fuels and electric charging station infrastructure, availability of alternative fuel vehicles (AFVs) and electric drive vehicles, and consumer reluctance to purchase new technologies.

In this fiscal year, we first examined the relationship between the availability of alternative fuels and station infrastructure. Specifically, we studied how EV charging infrastructure affects the acceptance of EVs compared to vehicles that rely on mature, conventional petroleum-based fuels. Second, we studied how the availability of less costly AFVs promotes their representation in the LDV fleet. Third, we used ParaChoice trade space analyses to provide information regarding which consumers are reluctant to purchase new technologies. Last, we began analysis of the impacts of alternative energy technologies on Class 7 and 8 trucks to isolate those that may most efficaciously advance heavy-duty vehicle (HDV) efficiency and petroleum use reduction goals.

Objectives

The lifetime project objective is to provide system-level analysis of the dynamics among the LDV and HDV fleets, fuels, infrastructure mix, and emissions. These capabilities have been instantiated in the ParaChoice model. The name ParaChoice is derived from the fact it is a *para*metric vehicle *choice* model. ParaChoice's parametric capabilities are used to identify trade spaces, tipping points, and sensitivities. Further, parametric analyses can help quantify the effects of and mitigate uncertainty introduced by data sources and assumptions.

LDV analysis goal: Determine the potential for AFVs to penetrate the market, reduce LDV petroleum consumption and emissions, and impact energy use. Determine factors that influence alternative energy vehicle penetration and impact, the path to more efficient vehicles, tipping points for impactful penetration, and sensitivities.

HDV analysis goal: Evaluate the potential for AFVs to increase freight hauling efficiency and reduce pollution, similarly to LDV. The capability to handle vocational HDVs were added to ParaChoice to facilitate these analyses.

Approach

ParaChoice models the system comprising energy sources, fuels, and LD or HD vehicles; see Figure II.2.1. Simulations begin with today's energy, fuel, and vehicle stock and projects out to 2050. At each time step, vehicles compete for share in the sales fleet based on value to consumers. The simulation assesses generalized vehicle cost for each vehicle at every time step. A nested multinomial logit choice function assigns sales fractions based on these costs and updates the vehicle stock accordingly; see Figure II.2.2.

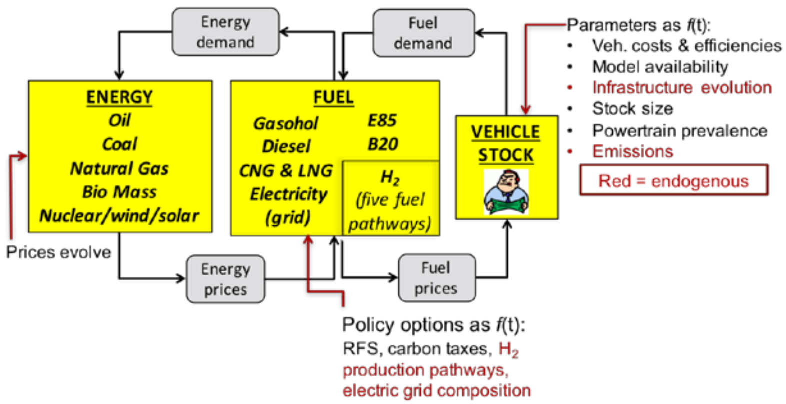

Figure II.2.1 - ParaChoice system dynamics model structure

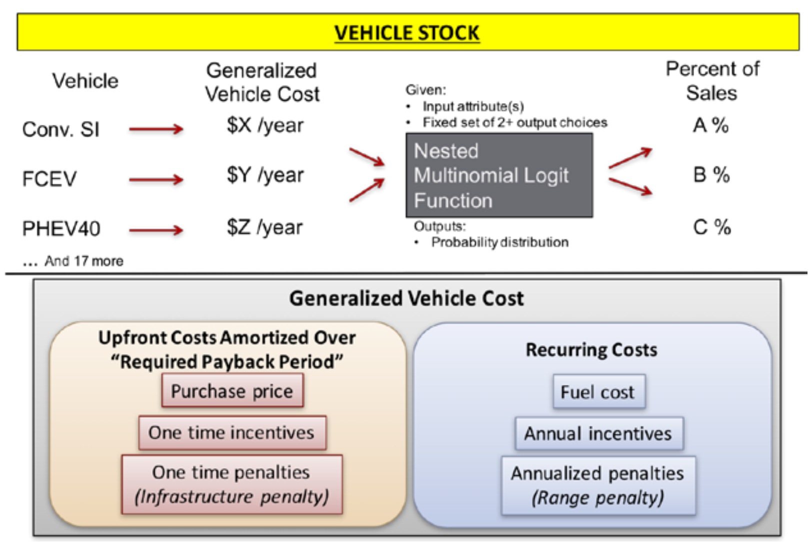

Figure II.2.2 - ParaChoice methodology for sales fraction calculation

Baseline input sources include: the AEO 2016 (energy prices); the GREET® model (emissions); the National Household Travel Survey (LDV fleet segmentation); Polk vehicle registration data (HDV fleet segmentation); Autonomie simulations (LDV price projections); the National Petroleum Council [1] (HDV price projections);

and Alternative Fuels Data Center (2010-2017 fueling stations and policies (by state)). Vehicles, fuels, and populations are segmented to study the competition between powertrains and market niches (see Figure II.2.3).

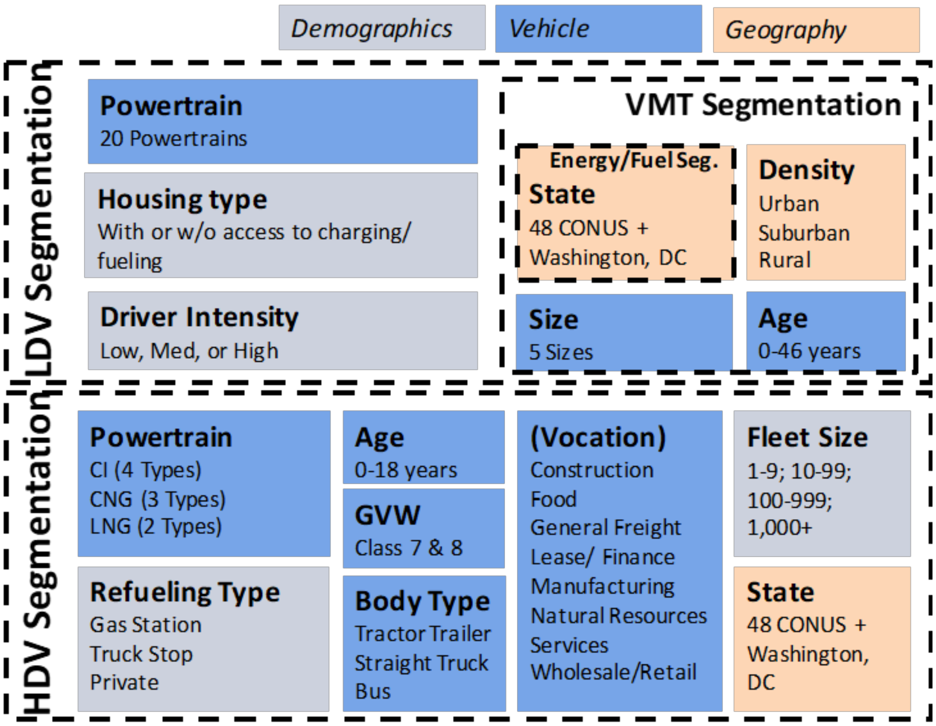

Figure II.2.3 - LD and HD vehicle segmentation in ParaChoice

ParaChoice is unique from other DOE vehicle choice models because it is designed to explore uncertainty and trade spaces, easily allowing identification of tipping points and sensitivities. Trade space analyses involve varying two parameters independently to generate approximately 400 scenarios covering all potential combinations across the ranges evaluated. Sensitivity analyses involve varying many parameters at once to generate approximately 3,000 scenarios. Parameterization ranges are designed to explore plausible and "what if?" regimes to provide thorough coverage of possible future states. Such analyses can provide: (1) perspectives in uncertain energy and technology futures, (2) sensitivities and tradeoffs between technology investments, market incentives, and modeling uncertainty, and (3) the set of conditions that must be true to reach performance goals.

Results

ParaChoice was used to create a "business as usual projection" using cost assumptions from Autonomie and the AEO 2016. It is important to note that ParaChoice projections are not the primary purpose of the model but are a starting point for understanding market drivers. This analysis showed modest penetration (~14%) of BEVs with 75, 100, 200, and 300 mile ranges by 2050 due primarily to a decrease in BEV purchase cost and fuel cost advantage to petroleum fuels; see Figure II.2.4. These results as well as others from additional ParaChoice model runs were made available through an interactive, online results viewer (https://h2-msm-vm.sandia.gov/parachoice) at the end of FY 2017.

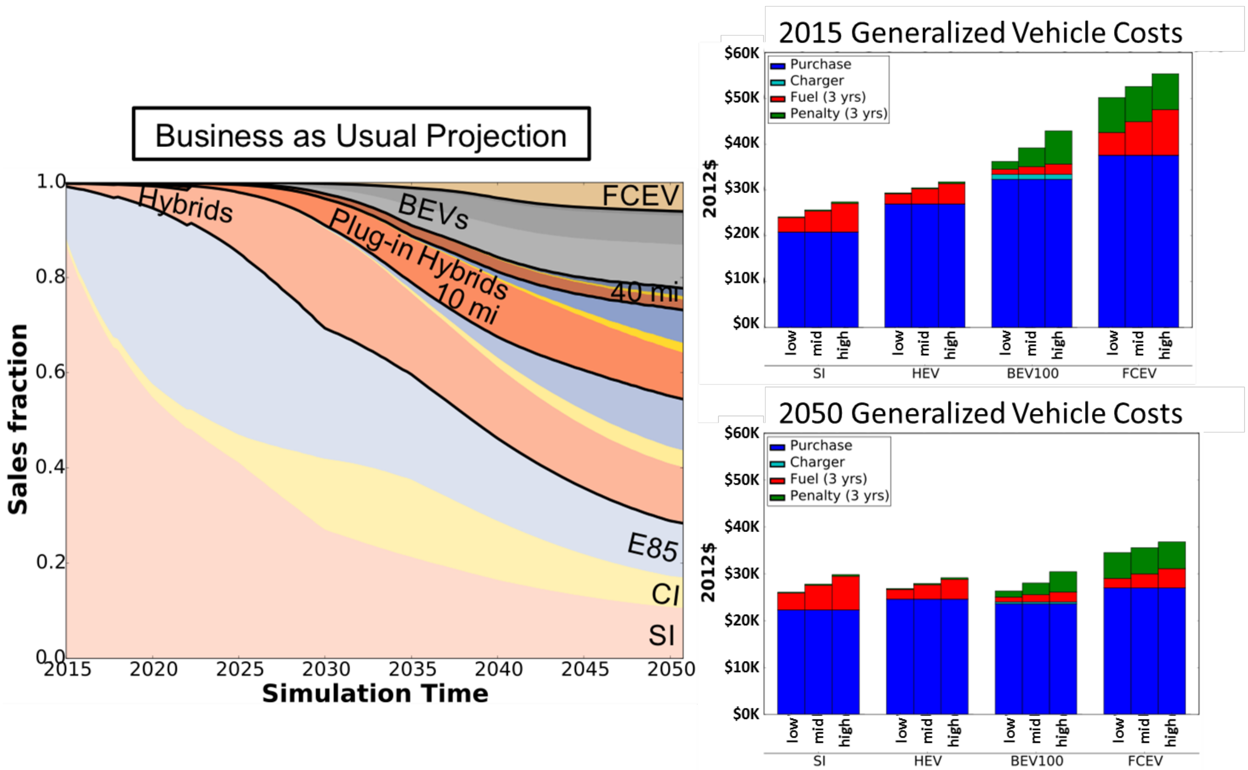

Figure II.2.4 - Baseline ParaChoice scenario analyses, including 2015 and 2050 generalized vehicle costs

We used ParaChoice to determine how various levels of public EV charging stations impact BEV sales and electrified miles traveled. For large scale national implementation strategies, public DC fast chargers were found to advance BEV sales more effectively than public L2 chargers, increase electrified mileage, and lower emissions, even if only one DC fast charging station is built for every ten L2 charging stations; see Table II.2.1. Further, adding a $0.10/kWh surcharge (over and above the cost to deliver the electricity) to consumers was found to severely dampen sales and electrified mileage gains.

Table II.2.1 - Impact of EV Charging Station Installations on BEV Sales and Electrified Miles Traveled

Powertrain	Baseline 2050 PT Sales Fraction (%)	Injecting 500K L2 (Δ%)	Injecting 50K DC Fast (Δ%)	50K DC Fast + $0.10/kWh Elec. Surcharge (Δ%)
SI, CI and E85	29	-1	-2	0
Hybrids	26t	0	-1	+1
Plug-in Hybrids	24	-1	-3	-1
BEVs	16	+1	+7	-1
FCEVs	6	0	-1	0
% of All Fleet Miles Electrified	15	+1	+8	+1

We also used ParaChoice to estimate energy savings for convenient charging (e.g., workplace L2 charging). The strengths of this method include: (1) incorporating and analyzing strategies for targeted infrastructure at the workplace, (2) recognizing the potential weaknesses of traditional infrastructure models for BEVs, and (3) Monte Carlo analysis to understand limitations of assumptions & confidence in trends. As the day-time charging range that is conveniently and reliably available to the population increases, fleet-wide petroleum use decreases in favor of other, purely domestic resources (see Figure II.2.5).

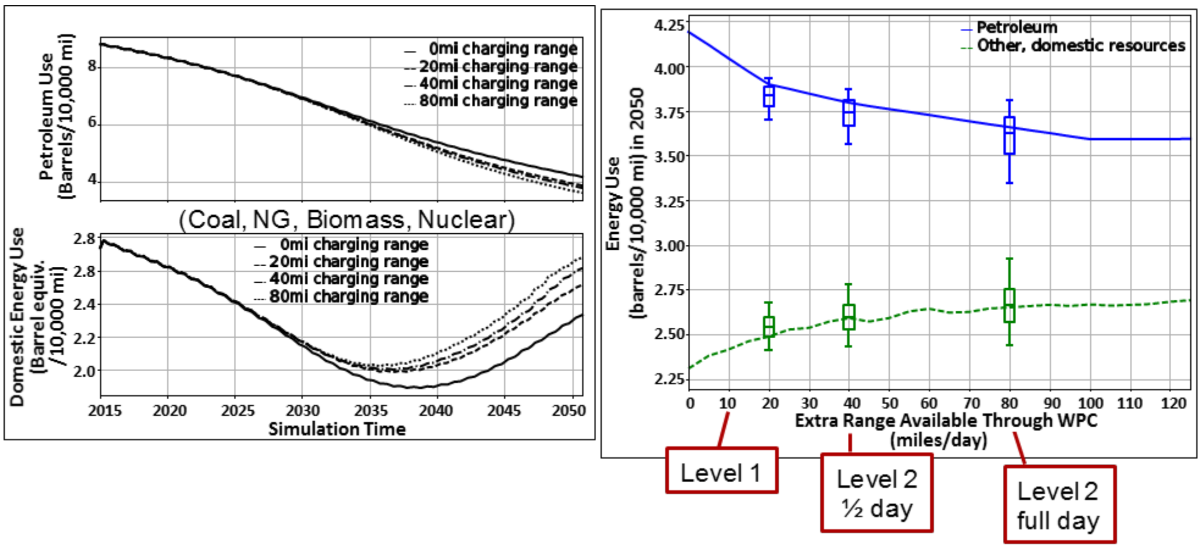

Figure II.2.5 - Energy and petroleum use varies with EV range extension due to convenient, day-time charging.

A trade space analysis of the impact on 2050 petroleum use of the fraction of population with access to day-time (e.g., L2 workplace) charging and maximum range extension due to such charging is shown in Figure II.2.6. This analysis shows that a large percentage of the population needs access to reliable L2 workplace charging in order to significantly reduce petroleum use by 2050, with the goal of energy independence, increased national security, and economic growth through affordable transportation.

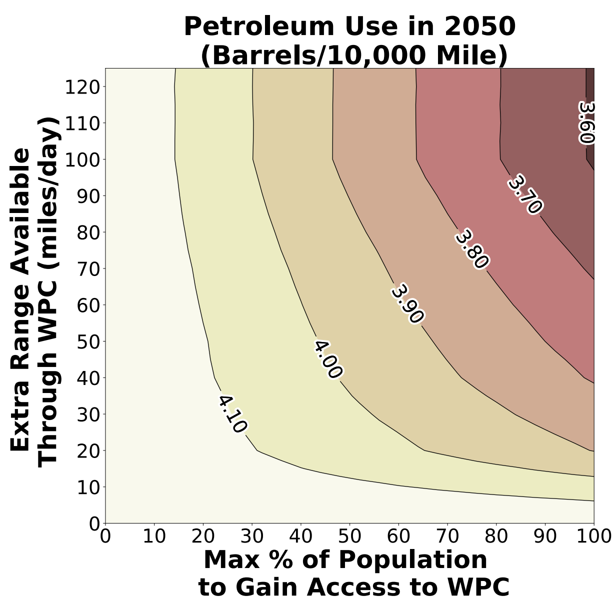

Figure II.2.6 - Workplace charging accessibility versus range trade space analysis

ParaChoice was used to explore the impact of natural gas (NG) fuel price on HDV powertrain adoption. The baseline assumption was that one-quarter of HDVs are NG powered. The fraction of HDVs in the fleet at the end of the simulation, 2050, did not change when a $0.50 fuel price reduction was applied through 2016. The natural gas vehicle (NGV) fraction in 2050 increased to one-third when the reduction was extended to 2050. As a bounding case, zero-cost fuel was required to increase the NGV fleet fraction to more than half; in which case, growth was primarily in liquefied NG powered vehicles. As such, we concluded practical NG price reductions have minimal impact on adoption on their own.

To establish the foundations of a more comprehensive assessment of the impact of new alternative energy technologies on HDV, we collected data (Polk 2011 and Vehicle Inventory Use Survey 2002) on Class 7 & 8 HDV segmentation and vocations including: vehicle stock, VMT, and fuel consumed; see Figure II.2.7. In parallel, we updated the ParaChoice model to greatly simplify adding new, user-specified segments/vocations. This was important because the HDV fleet is heterogeneous, and only some segments will be appropriate for new technologies based on stock or duty cycle. Technology benefits are quantified by multiplying the vehicle stock by the fuel savings (due to tractive effort, idling, or vocational load) or emissions (e.g., nitrogen oxides, sulfur oxides, or particulate matter) reduction. This work is continuing into FY 2019, where the various segments of the fleets can be analyzed for their suitability for electrification and efficiency improvement through replacement with other technology alternatives.

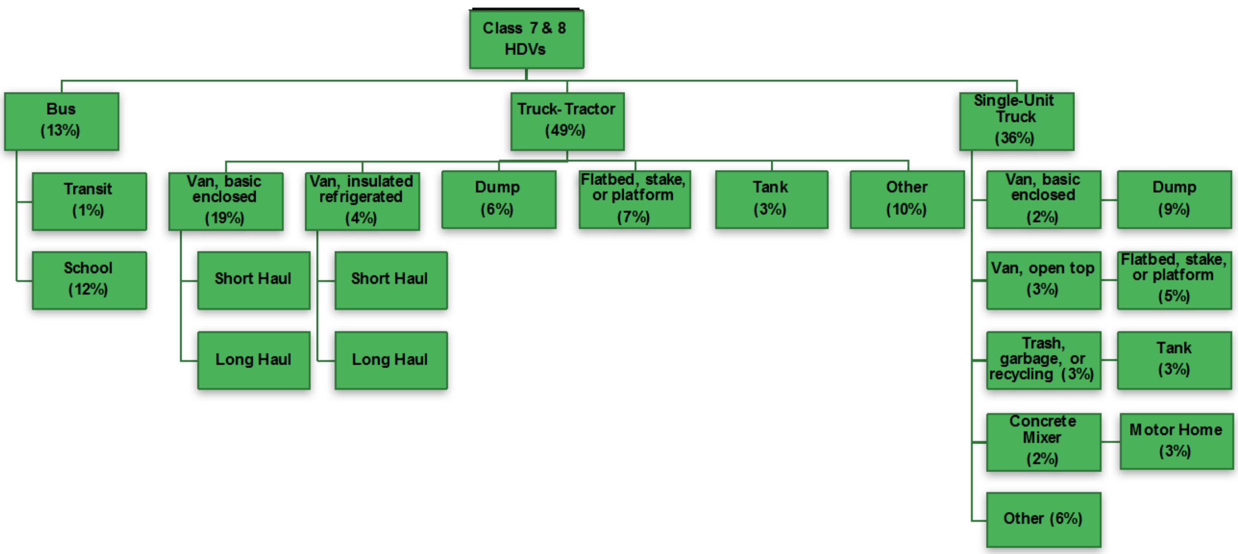

Figure II.2.7 - Class 7 & 8 HDV taxonomy with inset segmentation by vehicle stock

Conclusions

ParaChoice is a validated, system-level model of the dynamics existing among vehicles, fuels, and infrastructure. It leverages other DOE models and inputs to simulate fuel production pathways that scale with demand from vehicles. It is designed for parametric analysis in order to understand and mitigate uncertainty introduced by data sources and assumptions. Native parametric capabilities are also useful for identifying trade spaces, tipping points, and sensitivities. ParaChoice is not simply a tool for creating scenario sales projections. Its results help analysts understand relationships among the LDV and HDV stocks, fuel use, and emissions.

Key Publications

Levinson RS & West TH (forthcoming). "Impacts of Workplace and Other Convenient Day-Time Charging." *Manuscript in preparation.*

Levinson RS & West TH (forthcoming). "Impact of Public Electric Vehicle Charging Infrastructure." Manuscript submitted for publication in *Transportation Research Part D*, October 2016

References

1. NPC (2012). Advancing Technology for America's Transportation Future. National Petroleum Council, August 2012.

II.3 Market Dynamics Modeling – Household-level Vehicle Decision Modeling

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Start Date: October 1, 2016 End Date: September 30, 2018
Total Project Cost: $373,155 DOE share: $373,155 Non-DOE share: $0

Project Introduction

Vehicle ownership and transaction decisions are shaped over time by various factors including demographic characteristics, travel behavior, and built environment. The introduction of PEVs to the vehicle market further affects these vehicle decisions. In order to capture the vehicle decision process, we develop a dynamic model of household vehicle decisions in terms of vehicle transaction (including purchase a new or used vehicle, trade-in a vehicle, dispose of a vehicle, or do nothing) and vehicle fuel type (gasoline, hybrid gasoline electric, plug-in electric, and diesel). This model covers the lack of aggregate models of vehicle decisions at national, regional, or zonal level by capturing the household level factors. The household-level dynamic vehicle decision model can be used as an input of the activity-based Polaris platform developed by ANL for the Chicago and Detroit metropolitan areas. This platform offers adding realism to transportation system simulations, while taking advantage of detailed information on the vehicle ownership and individual-level activities.

Objectives

The project will provide a new, more fundamental, household LDV purchase decision model to project future purchases and resulting market shares by drivetrain technology over time.

Approach

Limitations of earlier aggregate models of vehicle decisions in capturing the behavioral process of the vehicle ownership decision motivated a disaggregate household-level modeling approach. In this approach, disaggregate discrete choice models describe how households' vehicle decisions are influenced by their lifestyle, travel pattern, and socio-economic characteristics, as well as built-environment factors. The majority of disaggregate discrete choice models are estimated using static data, which ignore how this process happens over time. Modeling the dynamics of household decision behavior with consideration of new vehicle technologies (i.e., PEV) requires panel data. The scarcity of a database containing both vehicle transaction and fuel type necessitates integration of two databases, the California Statewide Travel Survey (for vehicle type choice) and the Puget Sound Travel Survey from the State of Washington (for vehicle transaction choice). We recognize that PEV sales shares are much higher in California than in other states, but assume that decision behavior of California households is similar to that of other households, so that state-level differences in sales shares are driven by incentives and other market drivers in California, not by household decision behavior that is unique to California.

A two-stage connected framework is developed to model vehicle transaction and fuel type decisions. At the first stage, a two-level nested logit (NL) model determines the choice of vehicle fuel type (gasoline, hybrid, PEV, and diesel). The choice of vehicle transaction alternative (buy, trade, dispose, and do nothing) is modeled in another NL model at the second stage. The connection between the two stages is provided by including the log-sum (expected) value of the vehicle type model to the vehicle transaction model. The dynamic behavior of the vehicle transaction is considered in the framework by using two waves of a panel database.

Future work will refine the model framework, identify additional data to estimate model parameters, and compare model results with registration data and other data as available.

Results

Relevant literature has been reviewed, data sources identified, and possible model frameworks assessed for suitability (given available data sources). Preliminary models have been estimated based on data from selected sources.

Vehicle transaction and vehicle type choices are modeled in a connected two-stage framework. The first is a two-level NL model to give choice of vehicle type between four fuel types: gasoline, diesel, hybrid, and PEV. As shown in Figure II.3.1, the choice of fuel type is modeled in two levels. At the first level, the choice is either a traditional vehicle or a PEV. Here, PEVs include both PHEV and BEVs. Decision-makers who select traditional vehicle at the first level, choose one of the three fuel alternatives of gasoline, diesel, and hybrid vehicles at the second level.

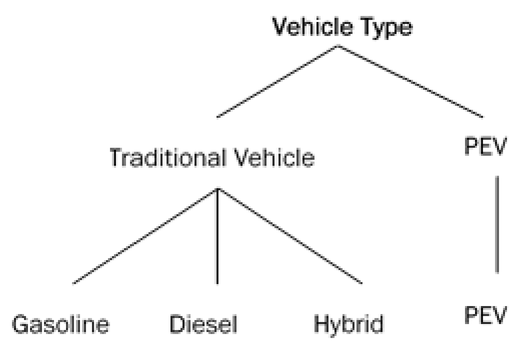

Figure II.3.1 - Vehicle type choice model structure
(Figure based on Nazari et al, 2017)

Vehicle transactions are modeled in the second stage framework using a sequential NL structure as used by Mohammadian and Miller [1], which is shown in Figure II.3.2. The choices in the upper level are transactions (do nothing, trade a vehicle, add a vehicle, or dispose of a vehicle). In the lowest level the choices are vehicle types. For households deciding to trade a vehicle, the choice of vehicle to dispose of is in the intermediate level.

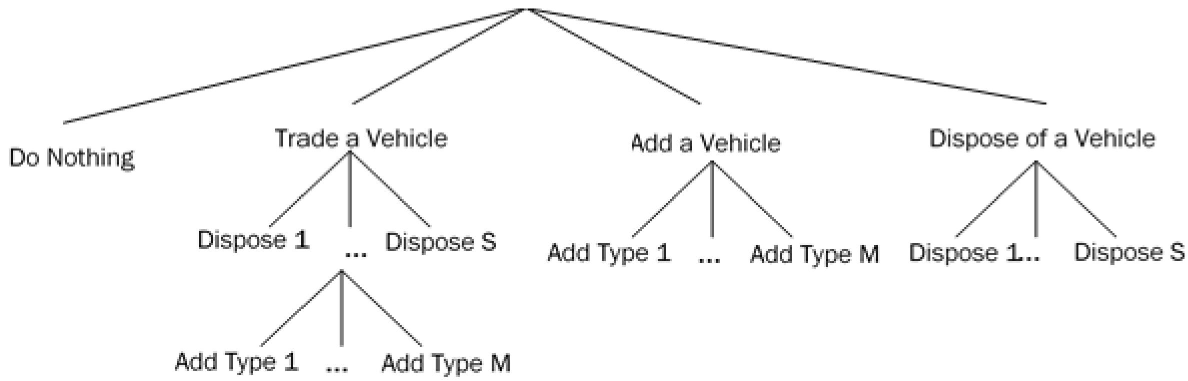

Figure II.3.2 - Vehicle transaction and type choice model structure
(Figure based on Mohammadian and Miller, 2003 [1])

The utilities from the vehicle type choice model (i.e., first stage) are considered in the utilities of decision-makers who choose adding or trading alternatives. These inputs are in the form of the logarithm of the summation of the utilities of the vehicle type model (known as inclusive value or log-sum). Furthermore, the type of the disposed vehicle for persons who select trade or dispose in the vehicle transaction model is determined by the explanatory variable of the age of the disposed vehicle.

The two-level NL vehicle type choice was estimated as described above, and the resulting parameter values are listed in Table II.3.1 for three groups of independent variables: socio-economic characteristics of households, built environment characteristics, and household travel behavior. Table II.3.1 also shows t-statistics, and almost all of the coefficients are significant at the 5% level.

From examining values of the coefficients, it is observed that choice of the PEV alternative is correlated with income and education level, and negatively correlated with household size and number of senior persons in the household. Interestingly, the PEV choice is correlated with the presence of car-sharing user(s) in the household.

As described above, a sequential NL was estimated to model the choice of vehicle transaction. The four vehicle transaction alternatives consist of do nothing, buy a vehicle, trade an existing vehicle for another one, and dispose of a vehicle. Five groups of independent variables (shown in the rows of Table II.3.2) include current socio-economic characteristics of the household, change in characteristics of households, fleet attributes, and land-use variables. This model also considers two latent variables as explanatory factors. The latent variable “green lifestyle” reflects the importance of bike, walk, and transit in the lifestyle of the household members. The other latent variable represents frequency of using car-sharing (e.g., Zipcar, Car2go) and ride-souring (e.g., Uber, Lyft) services as “mobility-on-demand preferences.” The estimated coefficients with the intuitive signs and values and the related t-statistics are presented in Table II.3.2.

Future work is planned to refine the model using additional data as they become available from surveys, such as a survey planned under separately-funded efforts by the University of Illinois at Chicago, and under the U.S. DOE SMART Mobility consortium Mobility Decision Science Pillar. Additionally, vehicle registration data and U.S. Census data for the Chicago metropolitan area, even if aggregated at the zip code level, can be used to check the probabilities given by the model.

Table II.3.1 - T Results of the Vehicle Type Model (t-Statistics are in Parentheses)

	Gas	Diesel	Hybrid	PEV
Constant		-3.057 (-41.53)	-2.546 (-35.59)	-5.807 (34.04)
Socio-economic characteristics of household				
Household size	0.156 (7.58)	–	-0.098 (-3.39)	-0.246 (-4.12)
# adult females > # adult males	0.582 (9.21)	–	0.712 (9.33)	0.230 (1.35)
Presence of a senior person (age ≥ 66)	0.184 (3.54)	–	0.086 (1.28)	-0.380 (-2.44)
Income < 75K	0.303 (8.22)	–	–	–
100K < income < 150K	–	–	0.240 (4.48)	0.272 (1.74)
150K < income < 200K	–	–	0.401 (6.21)	0.675 (3.90)
Income > 200K	–	–	0.559 (8.82)	1.141 (7.30)
# persons with bachelor degree	0.225 (7.12)	–	0.652 (15.78)	0.538 (6.36)
# persons with graduate degree or more	0.376 (9.88)	–	1.064 (23.05)	0.901 (9.29)
# of vehicles	-0.307 (-17.01)	–	-0.659 (-21.41)	–
Built Environment characteristics				
Residential type (single family attached house)				
Residential type (apartment)	0.844 (6.21)	–	0.915 (5.96)	–
Number of charging stations in County	1.363 (9.378)	–	1.133 (7.08)	–
Travel behavior of household				
Number of HH daily trips	0.019 (1.80)	–	0.089 (6.78)	0.044 (1.66)
Presence of transit user	0.213 (3.15)	–	0.250 (3.08)	0.248 (1.63)
Presence of car-sharing system user	-0.516 (-3.80)	–	–	1.784 (7.12)
Inclusive value				1.000 (fixed)

Inclusive value of TV nest = 0.757 (6.221)				
Log-likelihood at zero = -104,837.120				
Log-likelihood with constants = -25,377.840				
Log-likelihood at convergence= -23784.980				

Table II.3.2 - T Results of the Vehicle Transaction Model (t-Statistics are in Parentheses)

	Do nothing	Buy	Trade	Dispose
Constant	2.706 (9.14)	-1.889 (-3.44)	-1.555 (-3.46)	
Socio-economic characteristics of household				
Income > 100K		0.685 (2.55)	0.428 (2.09)	
Number of vehicles		0.547 (4.01)		
# driver license holders = # vehicles	1.566 (8.12)		1.938 (6.85)	
Commute mode of primary driver is car-alone				-0.557 (-2.13)
Change in household characteristics				
Household size +		1.319 (3.93)		
Household size -				1.209 (3.84)
Number of children +			0.938 (2.36)	
Number of children -			1.111 (2.61)	
Number of workers +		0.746 (2.14)		
Number of workers -				-0.640 (2.19)
Fleet attributes				
Age of vehicle in wave 1			0.058 (4.59)	0.066 (5.59)
Age of vehicle in wave 2, (new = yes)			0.501 (2.42)	

Latent variables				
Green lifestyle	0.188 (3.57)			
Mobility-on-demand preferences				0.432 (1.78)
Inclusive values		0.889 (3.34)	0.498 (2.78)	
Log-likelihood at zero = -3,325.7				
Log-likelihood with constants = -1,329.2				
Log-likelihood at convergence= -1,039.1				

Conclusions

A two-level NL model is employed to predict the vehicle type choice of households in terms of four fuel types: gasoline, diesel, HEV, and PEV. A NL vehicle transaction model with latent variables is estimated using two waves of a panel dataset, which accommodates four transaction decisions: buy, trade, dispose, and do nothing. The model was estimated based on two main data sources; the vehicle type choice model was estimated using data from the California Statewide Travel Survey, and the vehicle transaction choice model was estimated using the Puget Sound Travel Survey from the State of Washington.

Future work is planned to refine the model using additional data as they become available.

Key Publications

Nazari, F., A. K., Mohammadian, and T. Stephens. “Dynamic Household Vehicle Decision Modeling Considering Plug-in Electric Vehicles,” accepted for presentation at the Transportation Research Board 96th Annual Meeting, January, 2018, Washington, DC, and under revision for publication in *Transportation Research Record: Journal of Transportation Research Board*.

References

1. Mohammadian, A., and E. Miller. (2003) “Dynamic Modeling of Household Automobile Transactions,” Transportation Research Record: *Journal of the Transportation Research Board*, No. 1831, 2003, pp. 98-105.

II.4 VISION / NEAT Annual Update

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Start Date: October 1, 2016 End Date: September 30, 2017
Total Project Cost: $180,000 DOE share: $180,000 Non-DOE share: $0

Project Introduction

Developed with VTO support over the past 10+ years, the VISION/NEAT model (http://www.anl.gov/energy-systems/project/vision-model) addresses the need to assess fleet-wide energy and emission effects from market adoption of vehicle/fuel technologies. It does so by tracking historical patterns of vehicle travel, fuel use, and emissions by mode and vehicle size/type. The result is a profile of the U.S. vehicle fleet consistent with the EIA's AEO reference case, the U.S. Department of Transportation's (U.S. DOT's) Freight Analysis Framework (FAF), and a long-term forecast of advanced vehicle/fuel systems.

Relevance to VTO Analysis Program: The VTO Analysis Program has a long history of developing, improving, and applying models to support evaluations of VTO research and development (R&D) portfolios, DOE-wide studies like the Quadrennial Technology Review, multiagency activities and partnerships like U.S. DRIVE and SuperTruck, and broader efforts involving groups like the National Research Council. Tools to evaluate the impact of VTO's R&D portfolio on energy use, emissions, and cost of ownership are critical since they permit benefit estimation for the program at the national level.

Objectives

In FY 2017, ANL pursued three objectives:

1. Update VISION/NEAT to align the base case with annual AEO and FAF projections, and revise to reflect energy and emission coefficients from the latest GREET® model.

2. Develop a stochastic module for key parameters. Distribution functions for parameters like ton-miles, energy intensity by commodity and mode, mode share, and alternative fuel usage were developed.

3. Summarize the research results of scenario analysis of energy and emissions impacts due to mode shift from truck to rail in an ANL report.

Approach

Since vehicles, especially HD vehicles, are long-lived assets, the penetration of advanced vehicles/fuel systems into the total fleet can take decades. In addition, estimates of fleet-wide energy and emission effects must account for vehicle survival, technology trends, and macroeconomic factors, such as gross domestic product and energy prices. The VISION/NEAT model has been developed to serve this goal. In this task, ANL updated the model with historical data and data on trends related to market adoption, vehicle usage and efficiency, and mode shares by using the EIA's AEO and the U.S. DOT's FAF forecasts along with GREET® emission estimates. Efforts also were made to enhance the model's user interface, flexibility, and coverage.

Task 1. Annual update and upgrade of VISION/NEAT. VISION/NEAT was updated to align the base case with the AEO 2017 reference case and FAF4.0 projections. It was also revised to reflect energy and emission coefficients from the latest GREET® model release. VISION/NEAT structure was streamlined with an improved interface for presenting inputs and parameters relevant to user-defined scenarios, and for providing graphics and drop-down menu functions for users.

Task 2. Integration of uncertainty analysis. Key parameters in VISION/NEAT are subject to variations and uncertainties. In FY 2017, a stochastic module for HDVs was developed to systematically examine uncertainty ranges for key parameters. Data for developing stochastic model inputs was drawn from ongoing analyses of vehicle usage, survival functions, price, as well as industry sources.

Task 3. Scenario analysis with VISION/NEAT. ANL conducted a scenario analysis to quantify the energy and emission effects of mode shifts from truck to rail using the uncertainty analysis module in VISION/NEAT. ANL examined the commodity types that could be moved by rail or water instead of truck and evaluated the service availabilities of rail and water modes that could support such mode shifts. In FY 2017, ANL summarized the analysis results and published an ANL report (https://www.anl.gov/energy-systems/publication/evaluation-potential-shifting-freight-truck-rail-and-its-impacts-energy).

Results

Task 1 and 2: ANL updated and released the VISION 2017 model to users in November 2017. The VISION model is updated annually. The Base Case in the most recent version of the model reflects projections of LD and HD vehicles in EIA's AEO 2017. EIA's AEO 2017 projections end in the year 2050. In the 2017 VISION model update, these projections are extended to the year 2100. For emissions calculation, the VISION model uses full fuel cycle coefficients derived from ANL's GREET® model. This release includes the following expansions and updates:

- Added alternative powertrain technologies to medium- and heavy-duty (MD and HD) trucks, including plug-in gasoline electric, plug-in diesel electric, battery electric, and fuel cell electric vehicle (FCEV)
- Updated with emissions and upstream energy rates from GREET1_2017 (http://greet.es.anl.gov/)
- Updated with EIA AEO 2017 Reference Case
- Updated car and LD truck (commercial 2B truck included) survival functions due to the changes in EIA National Energy Modeling System model first implement for 2016 projections (http://www.eia.gov/forecasts/aeo/pdf/0383(2016).pdf)
- Updated historical Class 3-6 and Class 7&8 AFV sales and stock to match the data reported on EIA website (https://www.eia.gov/renewable/afv/).

Figures II.4.1 through II.4.3 illustrate the updated VISION base case results.

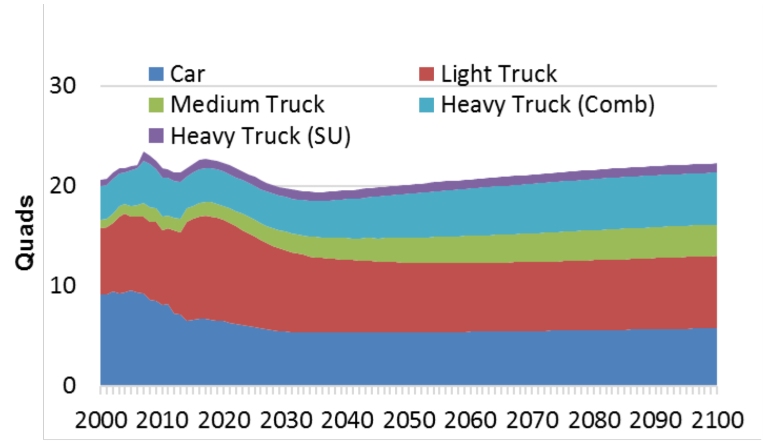

Figure II.4.1 - Long-term base case energy use by vehicle type

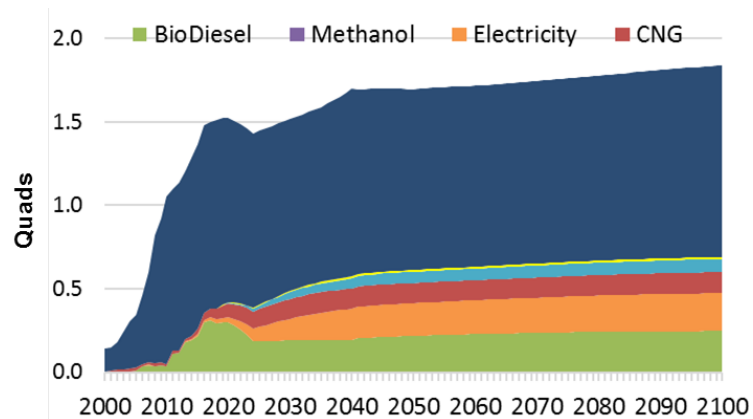

Figure II.4.2 - Long-term base case energy use by fuel type, oil excluded

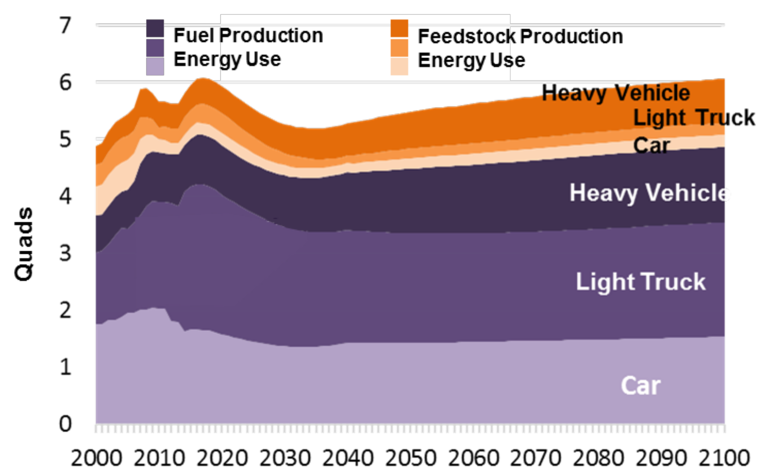

Figure II.4.3 - Long-term base case feedstock and fuel production energy use by vehicle class

Task 3: Under the baseline mode shift scenario, ANL found that a 4.3% net energy savings and a 4.4% reduction in emissions could be achieved by 2040. These small numbers result from restrictions imposed while developing the baseline scenario. First, we omitted many commodities owing to the low volume of their transport by truck traveling over 300 miles. Second, we assigned less than 100% mode shift potential to 10 out of 19 selected commodities. Third, we assigned 66% mode shift potential to excellent rail level of service, 33% to good rail level of service, and 10% to moderate rail level of service. Fourth, we selected truck freight going a distance longer than 300 miles. Finally, we selected origin-destination pairs with 10,000 tons or more going by truck. Note that the 4.3% energy savings and 4.4% emission reductions represent the national totals. Some individual origin-destination pairs may exhibit much higher percentages of energy-savings and emission-reductions. Figure II.4.4 shows the energy saving due to mode shift from truck to rail.

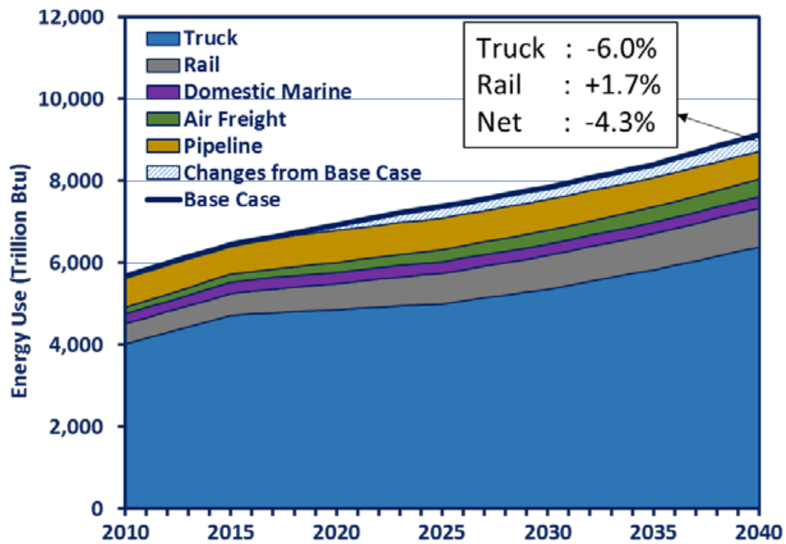

Figure II.4.4 - Energy use by mode (2010–2040)

Conclusions

ANL's VISION/NEAT model is fully updated to match with the projections in the AEO 2017 reference case and FAF4.0. Alternative powertrain technologies were added to MD and HD trucks in FY 2017. Historical vehicles sales, stock, fuel economy, and other information were collected and documented in the model.

ANL's freight shift analysis found only a 4.3% net energy savings and a 4.4% reduction in emissions could be achieved by 2040 through shifting from truck to rail.

Key Publications

Y. Zhou, A. Vyas and Z. M. Guo "An Evaluation of Potential for Shift of Freight from Truck to Rail and its Impacts on Energy Use and GHG Emissions", Draft report to DOE, March 2017.

II.5 Advanced Vehicle Cost and Energy-Use Model

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Start Date: October 1, 2015 End Date: September 30, 2019
Total Project Cost: $450,000 DOE share: $300,000 Non-DOE share: $150,000

Project Introduction

Advancing VTO's mission requires an understanding of how DOE-supported technologies are (or will be) used once adopted in the marketplace, both as a prerequisite for the retrospective calculation of investment effectiveness and resulting program benefits and for prospective evaluation of future technologies. As such, interest in the Advanced Vehicle Cost and Energy-use Model (AVCEM) model is aligned with the program's need to understand the external costs and benefits associated with advanced vehicle technologies. This interest supports achievement of DOE goals of petroleum consumption reduction, energy security, and energy affordability.

AVCEM is a multi-pathway model of energy use and lifetime cost for a wide range of advanced vehicle and fuel combinations. The model estimates manufacturing cost, associated retail cost, and total private and external lifetime cost of a vehicle designed to meet performance and range specifications (see Table II.5.1 and Figure II.5.1). It can be used to investigate the relationship between the lifetime cost(s)—the total cost of vehicle ownership and operation over the life of the vehicle, from both a private (consumer) and external cost (costs not borne by the vehicle owner) perspective—and important parameters in the design and use of the vehicle.

While AVCEM is a vehicle-design and vehicle lifetime-cost model, the model's cost capabilities in particular offer a unique opportunity to explore best practices in cost modeling, as well as methods for internalizing unpriced, displaced, or geographically and temporally diffuse costs (externalities), along with the results of doing both in concert. More specifically, the methodologies for expanding and improving the model will intentionally leverage a modular approach such that step-wise task-based report-outs offer useful understanding of the analytical issues associated with the development of individual modules. Furthermore, this also contributes to the final task, which, as the sum of the various modular prerequisite pieces, comprises the running of a final model for a comprehensive analysis of advanced vehicle lifetime cost.

Table II.5.1 - Fuel/Feedstock/Vehicle Combinations in AVCEM

Fuel –> ↓ Feedstock	*Gasoline*	*Methanol*	*Ethanol*	*Methane (CNG, LNG)*	*Propane (LPG)*	*Hydrogen (compressed)*	*Hydrogen (liquefied)*	*Hydrogen (hydride)*	*Electricity*
Petroleum	ICEV				ICEV				
	HEV								
Coal		ICEV				ICEV	ICEV	ICEV	
		FCEV				FCEV			
Natural gas		ICEV		ICEV		ICEV	ICEV	ICEV	
		FCEV				FCEV			
Wood, grass		ICEV	ICEV			ICEV	ICEV	ICEV	
		FCEV				FCEV			
Corn			ICEV						
Power generation						ICEV	ICEV	ICEV	BEV
	ICEV				ICEV				

ICEV = internal combustion engine; HEV = hybrid electric vehicle; FCEV = fuel-cell electric vehicle; BEV = battery electric vehicle. All FCEVs can be hybridized with a peak-power battery.

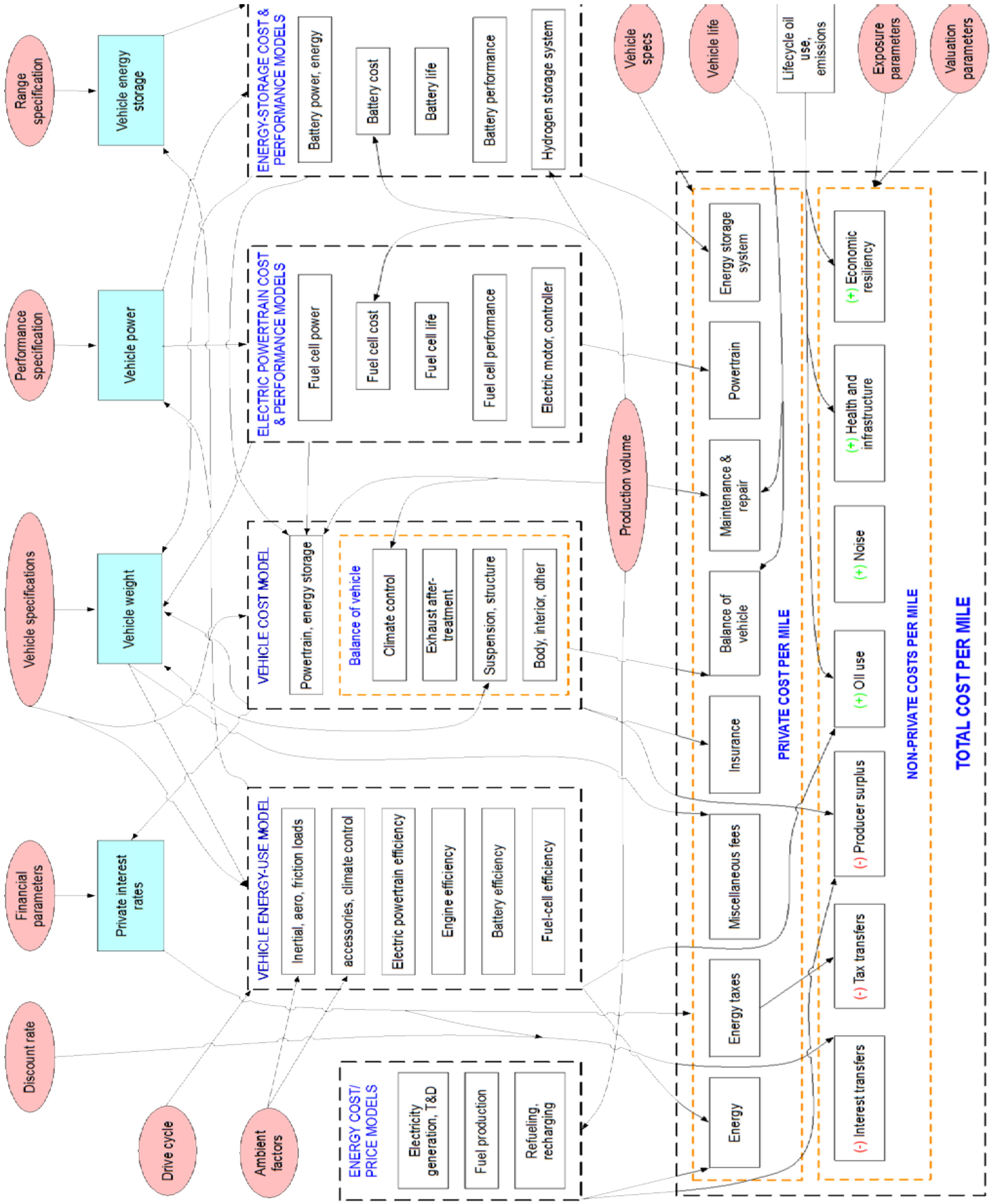

Figure II.5.1 - Structure of AVCEM

Objectives

As mentioned above, the development of AVCEM is intended to support a long-term effort to estimate advanced vehicle technology lifetime total costs to inform stakeholders and support DOE goals of emissions reduction and petroleum consumption reduction to improve affordability and national security.

Approach

This project will involve several tasks:

Task 1. Analysis of Discounting

We will present the conceptual underpinnings of the appropriate treatment of the discount rate in analyses of the lifetime cost of advanced vehicles, considering theoretical and empirical aspects. The analysis will recommend discount rate(s) for use in total lifetime-cost analyses.

Task 2. Analysis of Retail Cost vs. Manufacturing Cost

We will develop multiplier estimates specifically for converting vehicle sub-system manufacturing cost estimates to retail costs, with explicit consideration of differential multipliers for nascent technologies (i.e., batteries and hydrogen-storage systems) versus more mature technologies. The multiplier will expand on existing literature and account for estimates of all non-manufacturing costs (e.g., R&D, warranty, profit) up to the retail level result in an exhaustive and mutually exclusive set of cost categories.

Task 3. Battery Cost Model

We will develop a reduced-form version of the ANL Battery Performance and Cost (BatPaC) model, both for stand-alone use and for integration into AVCEM, wherein the reduced-form version will support optimization of vehicle lifetime cost given formal representations of trade-offs and interactions linked to battery design. Full documentation will accompany the model.

Task 4. Battery Lifetime Model

We will adopt, expand, and integrate version of the NREL battery lifetime model into AVCEM. The model will include a detailed representation of battery lifetime as a function of battery chemistry, charging conditions, temperature, discharge patterns, and other factors. Full documentation will accompany the model.

Task 5. External cost analysis

We will develop state-of-the art estimates of the external cost per mile of health and infrastructure impacts, noise, and fuel use for all fuel and vehicle combinations within AVCEM. We will create and incorporate a simplified version of the standard damage-function approach into AVCEM: estimate emissions or energy-use per mile, estimate changes in exposure and impacts, and estimate the value of impacts. We will build on our previous comprehensive total-cost analyses.

Task 6. Integration of PLEXOS®/BEAM and AVCEM

With separate funding, colleagues at Lawrence Berkeley National Laboratory (LBNL) are working on analyses of the interaction between EV charging and the electricity grid, using the grid model PLEXOS® and an EV charging model BEAM (the Framework for Behavior, Energy, Autonomy, and Mobility). However, because neither BEAM nor PLEXOS® include costs of the distribution system, and the cost estimates in PLEXOS® are not necessarily consistent with those in AVCEM, for the AVCEM project we will analyze the costs of electricity generation, transmission, and distribution system for use in linking PLEXOS®/BEAM with AVCEM.

Task 7. Complete and validate beta version of AVCEM

This task will include preliminary complete documentation.

Task 8. Comparison of full lifetime costs

Run AVCEM to estimate full private and external lifetime costs for all vehicle/fuel combinations in AVCEM.

Task 9. Develop a user-friendly version of AVCEM

Results

Because the AVCEM project is not scheduled to be finished until the end of FY 2019, the full model and its sub-components have not yet been completed. As a consequence quantitative technical results are not yet available.

Conclusions

Table II.5.2 summarizes progress made in FY 2017 under each AVCEM task.

Table II.5.2 - Summary of Progress on AVCEM Tasks in FY 2017

Task	Deliverable(s) by FY 2019	Highlights and Status, FY 2017; next steps
1. Discounting	• Report recommending discount rate(s) as a function of perspective and time-horizon	Reviewed literature, developed conceptual framework, began formal analysis of the discount rate, and began writing AVCEM documentation report. Next steps are to finish formal analysis and documentation report.
2. Retail vs. Manufacturing Cost	• Report recommending retail-price-equivalent multipliers for nascent and mature technologies, and details of underlying accounting.	Completed literature reciew, developed formal models, and began organizing materials for AVCEM documentation report. Next steps are to finish formal models and continue documentation.
3. Battery Cost	• Reduced-form version of ANL's BatPaC model • Model documentation	Completed final version of reduced-form BatPac model (with colleagues at UC Davis). Continued collaboration with German colleagues who are developing a similar cost model. Began writing AVCEM documentation report. Next step is to complete documentation report.
4. Battery Lifetime	• Revised and expanded version of NREL's battery lifetime model • Model documentation	Continued major review and revision of battery lifetime model and draft report. Continuing to work closely with scholars from Germany who are developing a similar model and collecting extensive test data. German scholar visited Berkeley in Fall 2017 to continue collaboration. Next steps are to perform additional battery-aging tests, analyze results, and prepare model documentation.
5. External cost	• Report on external costs of advanced vehicles	Continued work on models of external costs of energy use and producer-surplus component of oil prices. Continued updates to analysis of health and infrastructure impacts in AVCEM. Continued updates to estimates of valuation functions. Began organizing materials for AVCEM documentation report. Next steps are continued work in all areas.
6. Integration of PLEXOS/BEAM and AVCEM	• Incorporate model into completed and documented final version of AVCEM	Continued analysis of costs of electricity generation, transmission, and distribution system for use in linking PLEXOS/BEAM with AVCEM. Next steps are to continue work on performance and cost analysis of electricity distribution system.

7. Complete and validate beta version of AVCEM	• Complete revised version of AVCEM with documentation	Began work on revisions to key aspects of AVCEM. Will continue this work through FY18.
8. Comparison of full lifetime costs	• Report on full lifetime costs of advanced vehicles	FY18 project.
9. User-friendly version of AVCEM	• Publicly available version of AVCEM	FY19 project.

Key Publications

Mark A. Delucchi, *AVCEM: Advanced-Vehicle Cost and Energy-use Model, AVCEM Documentation, Overview of AVCEM*, Institute of Transportation Studies, University of California, Berkeley, CA (2017).

Mark A. Delucchi, *AVCEM: Advanced-Vehicle Cost and Energy-use Model, AVCEM Documentation, External Costs and Other Adjustments to Social Cost*, draft report for DOE, Institute of Transportation Studies, University of California, Berkeley, CA (2017).

Mark A. Delucchi, *AVCEM: Advanced-Vehicle Cost and Energy-use Model, AVCEM Documentation, Model of Battery Performance, Cost, and Lifetime*, draft report for DOE, Institute of Transportation Studies, University of California, Berkeley, CA (2017).

II.6 GREET®

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Start Date: October 1, 2016 End Date: September 30, 2017
Total Project Cost: $454,000 DOE share: $454,000 Non-DOE share: $0

Introduction

Life cycle analysis (LCA) is a platform for evaluating the sustainability of advanced vehicle-fuel systems. With support from several DOE offices, including VTO, since 1995, ANL developed the GREET® model to conduct LCA of a variety of vehicle/fuel systems. GREET® models fuel cycle, vehicle manufacturing cycle, and vehicle operation to provide estimates of life cycle energy use by type, emissions, and water consumption. By building on the existing GREET® modeling platform and the accumulated expertise at ANL (a VTO AP core capability), this project addresses new and emerging vehicle/fuel technologies (1) to quantify progress toward reducing transportation-sector life-cycle petroleum use and emissions via improved vehicle efficiency and fuel substitution, and (2) to identify energy- and emissions-intensive stages in the fuel and vehicle cycles for R&D priorities. Below are the updates made to GREET® in FY 2017.

In particular, electricity pathways in GREET® were expanded to include combined heat and power (CHP) generation, and options for carbon capture and storage (CCS) for coal and NG power plants. The generation efficiency and criteria air pollutant CAP emission factors of coal-based integrated gasification combined cycle power plants were also updated.

GREET® water consumption rates were used to develop a regional characterization factor (CF) representing the relative water scarcity to evaluate the impact of water consumption by energy systems. The available water remaining (AWARE) approach was further developed for the contiguous United States (AWARE-US) by incorporating measured runoff and human water consumption (HWC) data at the U.S. county level into the CF calculations.

GREET® was used to quantify the cumulative energy use and emissions benefits of PEVs since their introduction in different regions in the United States compared to gasoline ICEVs. PEVs include both BEVs and PHEVs. The analysis utilizes a spatial-temporal framework to evaluate the life cycle emissions associated with these vehicles in different U.S. regions and in different time periods (i.e., current and future).

Objectives

The objective of GREET® modeling is to inform VTO and stakeholders of critical energy issues for each vehicle/fuel technology under consideration, and to identify R&D areas needed to achieve VTO program's energy consumption reduction targets.

Approach

GREET® LCA covers a wide range of current and advanced vehicle/fuel technologies, including those with potential for future implementation in the United States and other global regions. GREET® addresses every aspect of the vehicle and fuel life cycles, including manufacturing, end-of-life disposal (recycling and scrappage), and vehicle operation, as well as fuel feedstock production and transportation, fuel production, and fuel distribution. Figure II.6.1 shows the main life cycle stages covered by the fuel cycle model (GREET1) and the vehicle cycle model (GREET2).

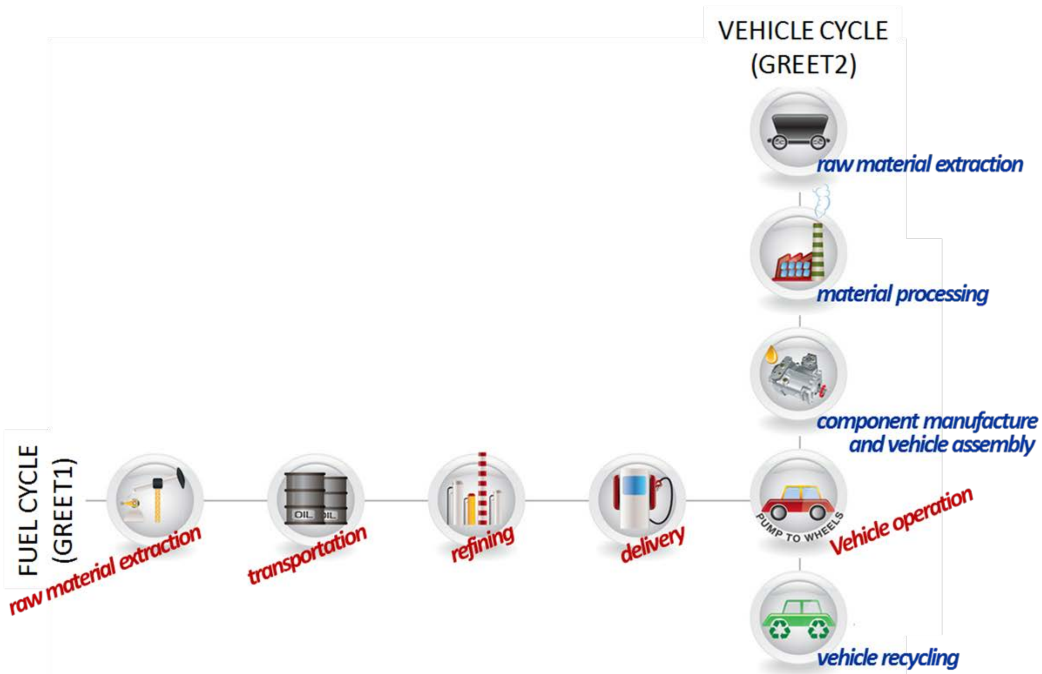

Figure II.6.1 - GREET® fuel cycle and vehicle cycle modeling approach

For the CHP expansion in GREET®, EIA power plant data from Form 923 (2015 data files) was used to determine the efficiency of several NG and coal CHP technologies. The Form 923 Generation and Fuel data was screened to identify steam turbine, gas turbine, or combined cycle facilities for NG, and steam turbine facilities for coal. A production weighted average of efficiencies of all plants within each generation technology determined characteristic plant efficiencies for the three types of NG plants and the one type of coal plants.

For the CCS configurations incorporated in GREET® for power generation technologies, we considered two possible CCS technology options for both coal steam turbine and NG combined cycle power plants: the integrated design option and the auxiliary power plant option. In the integrated design option, the heat for carbon dioxide (CO_2) regeneration from the absorbent and the electricity required for the CO_2 compression are sourced from the steam and electricity generated within the same power plant. In the auxiliary plant design, the heat and electricity required for the CCS are primarily sourced from an auxiliary power plant sized for that purpose.

The AWARE-US CF, a midpoint water stress indicator, was adopted to quantify water scarcity in a given region relative to a reference that represents weighted average water scarcity of all U.S. regions. The AWARE CF is the inverse of remaining available water, so high CF values are representative of water-stressed areas. The remaining available water is estimated to be the freshwater supply (as represented by natural runoffs) minus demand in each watershed; this amount represents the freshwater resources that can be sustainably used for other purposes. Water supply is used to meet the human and environmental water demand in a region. The environmental water requirement is the amount of water required to sustain the freshwater ecosystem services, and thus should be excluded from resources available for HWC.

For PEV benefit analysis, the characteristics of all BEV and PHEV models registered within each state from 2010 to 2015 were examined and a sales-weighted average vehicle for each North American Electric Reliability Corporation region was developed. BEVs and PHEVs within a given region were simulated via the GREET® model to determine their life cycle emissions. Those were then combined to develop a sales-weighted national average to compare against gasoline ICEVs, and also to the differences between region-based analysis and U.S. average analysis PEV evaluation.

Results

Figure II.6.2 shows the life cycle emissions for the U.S. average generation mix in 2016 and for individual coal and NG power generation technologies, including CHP and CCS technology options. The figure shows that the CHP technology option reduces emissions by 250 and 270 gCO_{2e}/kWh for coal and NG steam turbine generation technologies, respectively, and by a smaller 90 gCO_{2e}/kWh for the more efficient NG combined cycle technology. Integrated CCS technology option reduces emissions by 860 gCO_{2e}/kWh when applied to coal boiler technology and 340 gCO_{2e}/kWh when applied to the low emitting NG combined cycle technology.

Figure II.6.3 shows the AWARE-US CFs for the United States at the county level. Counties that appear white on the map are where water stress is less than the U.S. average (CF < 1), while red counties experience significant water scarcity. The map shows that the central and southwestern United States have high water CFs, while eastern regions tend to have CFs less than the U.S. average. Due to water consumption for irrigation, some counties around the Lower Mississippi River Basin have slightly higher CF values than neighboring counties, even though their natural runoff is relatively high. Some counties have a CF of 100, which means available freshwater resources are very limited in those counties and are likely in full use to meet their current HWC. In these counties, increase in HWC may incur groundwater depletion or may tap into the environmental water requirement causing degradation of aquatic ecosystems. Therefore, future implementation of technologies with low or no water consumption should be considered in these regions.

Figure II.6.4 shows the life cycle emissions of gasoline ICEVs and PEVs in various regions with the electricity generation mix of 2015. The life cycle emissions include both fuel cycle and vehicle cycle. The figure indicates that there is a great deal of spatial variation across utility regions where PEVs are implemented. However, the difference between the emissions of sales-weighted average PEVs and the U.S. average PEVs are not extremely large, suggesting that using a U.S. average generation mix for PEV evaluation provides a good representation of PEV emissions impacts. Results further suggest that both BEVs and PHEVs afford life cycle emissions benefits over their ICEV counterparts. With the increased penetration of renewable electricity in different regions, the life cycle emissions associated with PEVs will proportionally decrease.

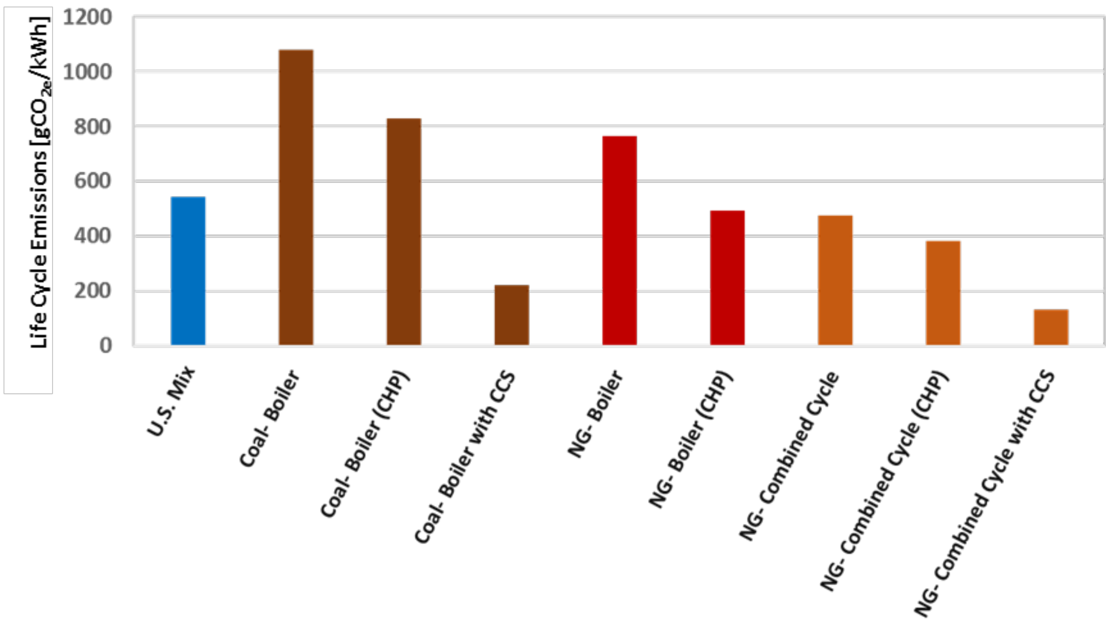

Figure II.6.2 - Life cycle emissions of electricity for U.S. average generation mix in 2016, and for individual coal and natural gas power generation technologies (including CHP and CCS technology options)

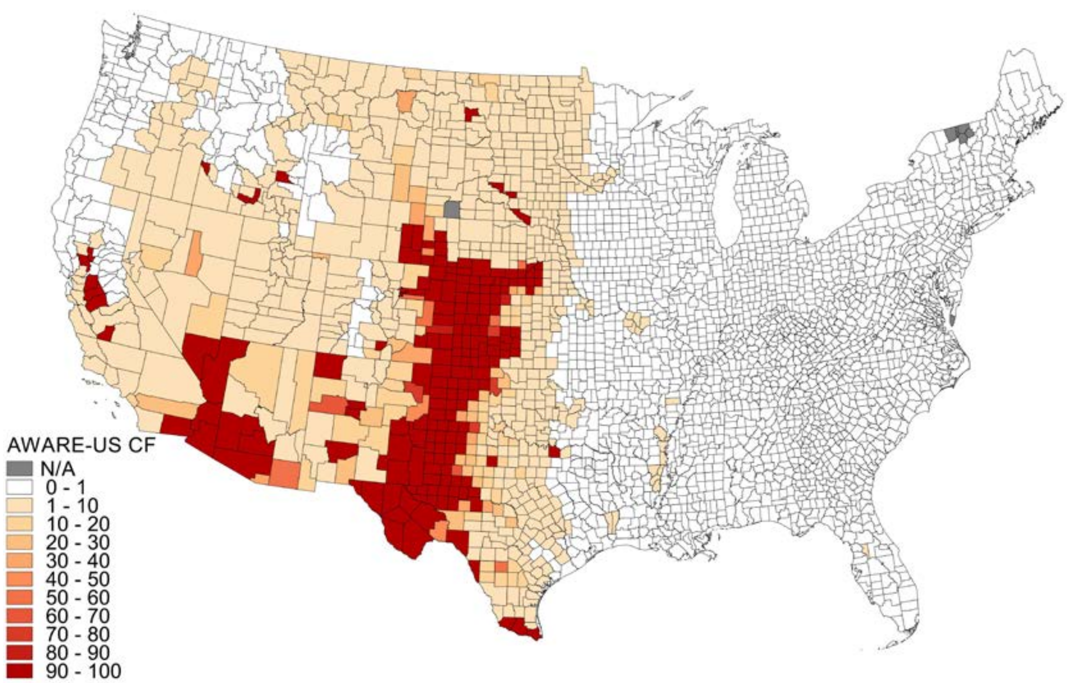

Figure II.6.3 - AWARE-US characterization factor at the U.S. county level

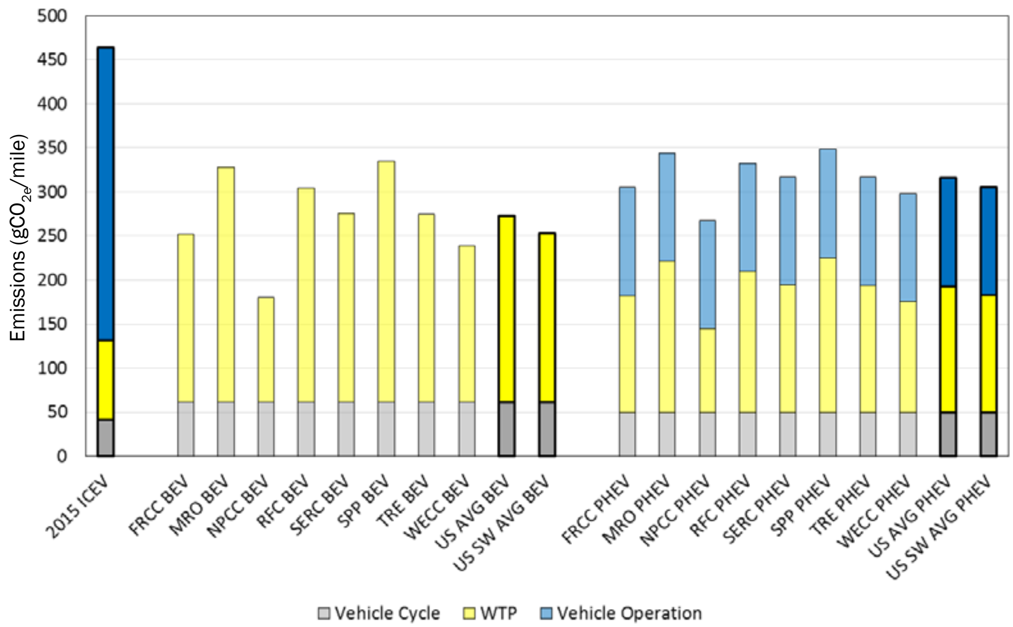

Figure II.6.4 - Life cycle emissions from BEVs and PHEVs in different utility regions in the United States in 2015 compared to gasoline ICEVs
(FRCC: Florida Reliability Coordinating Council; MRO: Midwest Reliability Organization; NPCC: Northeast Power Coordinating Council; RFC: Reliability First Council; SERC: SERC Reliability Corporation; SPP: Southwest Power Pool; TRE: Texas Reliability Entity; WECC: Western Electricity Coordinating Council; AVG: average; SW AVG: sales-weighted average)

Conclusions

Electricity pathways in GREET ®were expanded to include CHP generation, and options for CCS for fossil coal and NG power plants. GREET® water consumption factors were used to develop a regional CF representing the relative water scarcity to evaluate the impact of water consumption by energy systems. More information on data sources, models used, methodology, and key findings can be accessed through GREET® 2017 report (see key publications below). As an annual effort, the well-to-wheels calculator presenting well-to-wheels results of key vehicle/fuel options was updated with GREET® 2017 and posted at the GREET® website (https://greet.es.anl.gov/results).

Key Publications

ANL produced several publications during FY 2017 with VTO AP supports. These publications are summarized in the GREET® 2017 report listed below.

Wang, M., Elgowainy, A., Han, J., Benavides, P.T., Burnham, A., Cai, H., Canter, C., Chen, R., Dai, Q., Kelly, J., Lee, D., Lee, U., Li, Q., Lu, Z., Qin, Z., Sun, P., Supekar, S.D., 2017. Summary of Expansions, Updates, and Results in GREET® 2017 Suite of Models (No. ANL/ESD-17/25). Argonne National Laboratory, Argonne, IL. (https://greet.es.anl.gov/publication-greet-2017-summary).

II.7 Personalized Fuel Economy Calculator

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Start Date: October 1, 2016 End Date: October 1, 2017
Total Project Cost: $200,000 DOE share: $200,000 Non-DOE share: $0

Project Introduction

Informed consumer choice will help advance the adoption of efficient technology, which will help the DOE meet its mission of energy security. This project develops and validates a personalized fuel economy calculator to provide a decision support tool to help inform the purchase decision for car buyers.

For car buyers, the calculator measures a user's individual travel profiles, and predicts the fuel economy they would achieve in any car they are considering for their own driving. Users can apply the system to compare how much money they save over time in fuel across any car they are considering, which enables them to understand the long-term value of choosing a more efficient vehicle. This will help reduce petroleum imports, which makes up 49% of petroleum used in the transportation sector. In return, the US will see improved national security and economic growth.

Objectives

This project aims to further the development of the personalized fuel economy calculator, a tool that shows individual drivers how different vehicles save fuel, energy, and (potentially) money, while suiting their individual driving needs.

FY 2017 efforts had a significant focus on model validation of the vehicle physics models underlying the tool. Through further development, validation, and refinement of the underlying models, we worked to achieve U.S. Environmental Protection Agency targets of accuracy within 10% of actual on-road fuel consumption for the majority of trips.

Approach

Vehicle physics models were formulated and calibrated for conventional vehicles, HEVs, PHEVs, and BEVs, using methodologies developed under Berkeley Laboratory Directed Research and Development funds. Physics models were calibrated for nearly 6,000 vehicles, covering nearly every car from model years 2010-2017.

Under this project, validation of the physics models was conducted using on-road and chassis dynamometer data for over 50 vehicles spanning over 3,000 individual trips. Actual fuel consumption for each vehicle on each trip was calculated using experimental measurement data. The same on-road and chassis dynamometer driving cycles (i.e. speed and terrain vs. time profiles) were fed into the system's physics models. The actual and predicted fuel consumption was examined on time-resolved and trip-resolved levels to assess the accuracy of the models. Time-resolved measurements were used to identify sources of error that allowed further improvements to the mathematical models.

Results

Validation of the calculator's models against on-road and chassis dynamometer measurement data showed that the models were accurate on average within 10% of the actual on-road fuel consumption. A summary of the validation activities from this project is shown in Figure II.7.1B in comparison to federal fuel economy labels (Figure II.7.1A).

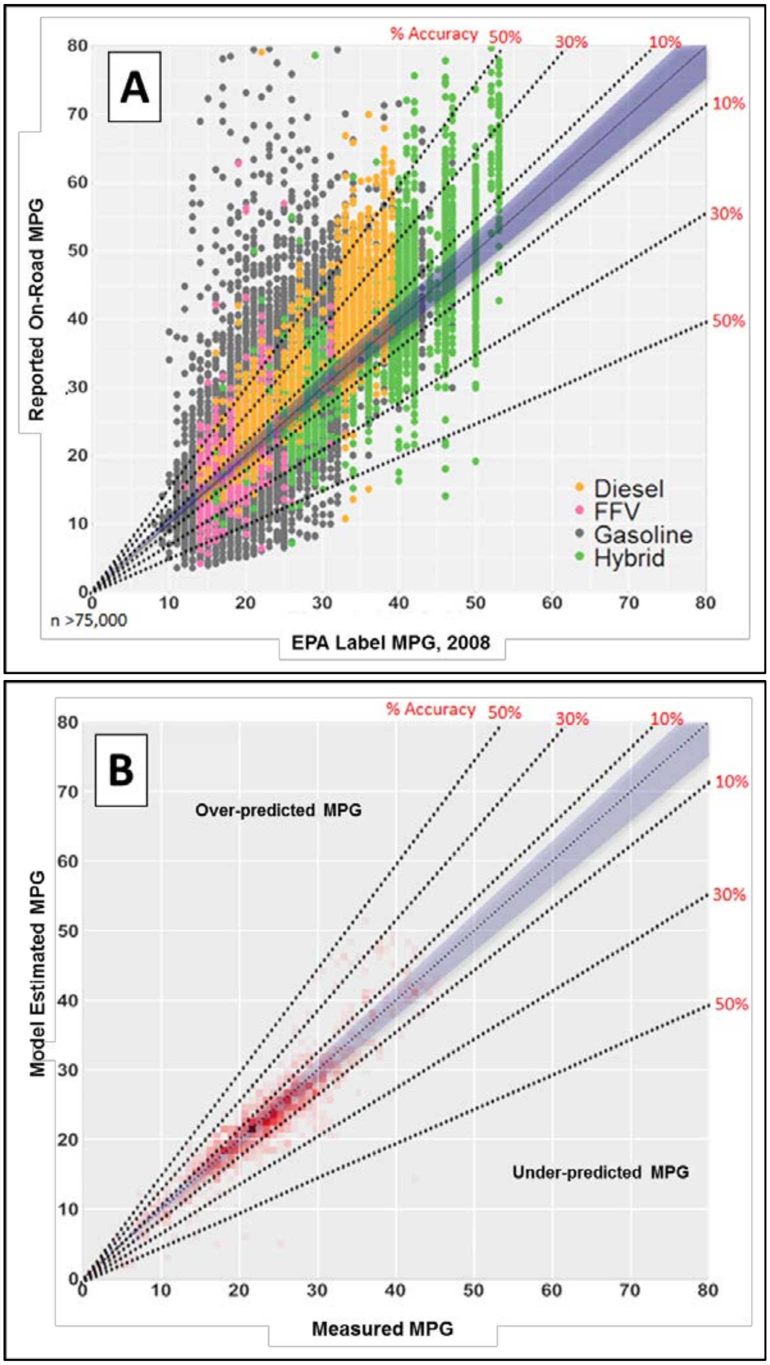

Figure II.7.1 - Comparing the accuracy of today's state of the art (the federal fuel economy label) versus model prediction. If on-road fuel economy is perfectly predicted, data clusters along the diagonal.
Figure A from D. Greene et al. [1]. Figure B is generated from model validation work under this project.

Conclusions

In this project, the personalized fuel economy calculator modeling methodology was validated against on-road and chassis dynamometer data representing a wide range of real-world driving conditions. The results showed that the model methodology substantially improves estimates of on-road fuel economy versus today's state of the art.

References

1. Greene, D.L., A.J. Khattaka, J. Liu, X. Wang, J.L. Hopsond, and R. Goeltze (2017) What is the evidence concerning the gap between on-road and Environmental Protection Agency fuel economy ratings? *Transport Policy*, 53, p. 146-160.

III. Applied Analysis of Vehicle Technology Benefits

III.1 Prospective Benefits Analysis for Fiscal Year 2018

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Start Date: October 1, 2016 End Date: September 30, 2019
Total Project Cost: $238,370 DOE share: $238,370 Non-DOE share: $0

Project Introduction

VTO and EERE's Fuel Cell Technologies Office (FCTO) research portfolio includes advancements in batteries; vehicle electrification; engines; fuels; materials; energy-efficient mobility systems; hydrogen production, delivery, and storage; and hydrogen fuel cells. Potential future benefits resulting from achievement of program goals and market adoption of technologies resulting from these research and development programs were estimated out to the year 2050. VTO uses results of this analysis to communicate the benefits of the program to DOE management, other agencies, Congress, and other stakeholders.

Objectives

The objectives of the project are to estimate potential future benefits attributable to the VTO program, while considering synergies and interactions with the FCTO Program. Estimated benefits include:

- Reduction in petroleum dependence resulting in increased national security and energy reliability
- Emissions reduction resulting in lower future mitigation costs
- Increased energy and transportation affordability resulting in economic growth

These benefits are estimated under assumed future conditions, and the sensitivity of the estimates to these assumptions is being evaluated.

Approach

Scenarios of successful development and introduction of advanced vehicle technologies were developed and analyzed, comparing a case with completely successful achievement of VTO and FCTO technology goals ("Program Success" case) to a case where there is no contribution after FY 2017 by the VTO or FCTO to development of these technologies ("No Program" case). Benefits were disaggregated by individual program technology areas, which included the FCTO and VTO research and development programs.

Sensitivity of these results to assumptions about technology performance was assessed by evaluating side cases with varying assumptions. Recognizing the uncertainty in the future market adoption of advanced-technology LDVs, four sets of LDV market shares by powertrain technology were developed using four consumer vehicle choice models. These were used to estimate ranges of benefits of VTO and FCTO programs for technologies implemented in LDVs. For MD and HD vehicles, market penetration projections of advanced technology packages within three size classes were estimated for the Program Success case using a single market penetration model. The resulting fleet fuel economy was compared to a No Program case developed from the EIA's AEO 2016 reference case with adjustments to represent the removal of DOE research and development support.

Results

Projections for the Program Success case indicate that by 2035, the average fuel economy of on-road, LDV stock could be 24% to 30% higher than in the No Program case. In addition, average on-road MD and HD vehicle stock fuel economies in the same year could be as much as 13% higher. The resulting petroleum savings in 2035 were estimated to be as high as 1.9 million barrels per day, and reductions in emissions were estimated to be as high as 320 million metric tons of carbon dioxide equivalent (CO_{2e}) per year. Such petroleum reductions result in significant reductions in fuel expenditure for both LD and HD vehicles, totaling approximately $100 billion annually by 2035.

Figure III.1.1A shows the projected petroleum consumption in years 2035 and 2050 under both the No Program and Program Success cases, with uncertainty bars showing the range of projected values. This report documents a robust range of benefits by using four LDV choice models to develop projections of future technology adoption and resulting petroleum use. Figure III.1.1B shows the range of projected cumulative petroleum savings after 2019 attributed to all VTO and FCTO technology programs. The upper and lower bounds in Figure III.1.1 represent the uncertainty in future market adoption of advanced-technology LDVs as estimated by four different consumer choice models.

VTO and FCTO technology is projected to improve fuel economy by 36% to 66% for new LDVs sold in 2035, and by as much as 77% by 2050, relative to improvements in the absence of DOE funding. Similarly, Program Success for new HD trucks would increase fuel efficiency by 24% by 2035, and 28% by 2050, relative to the No Program case. These increases are shown in Figure III.1.2.

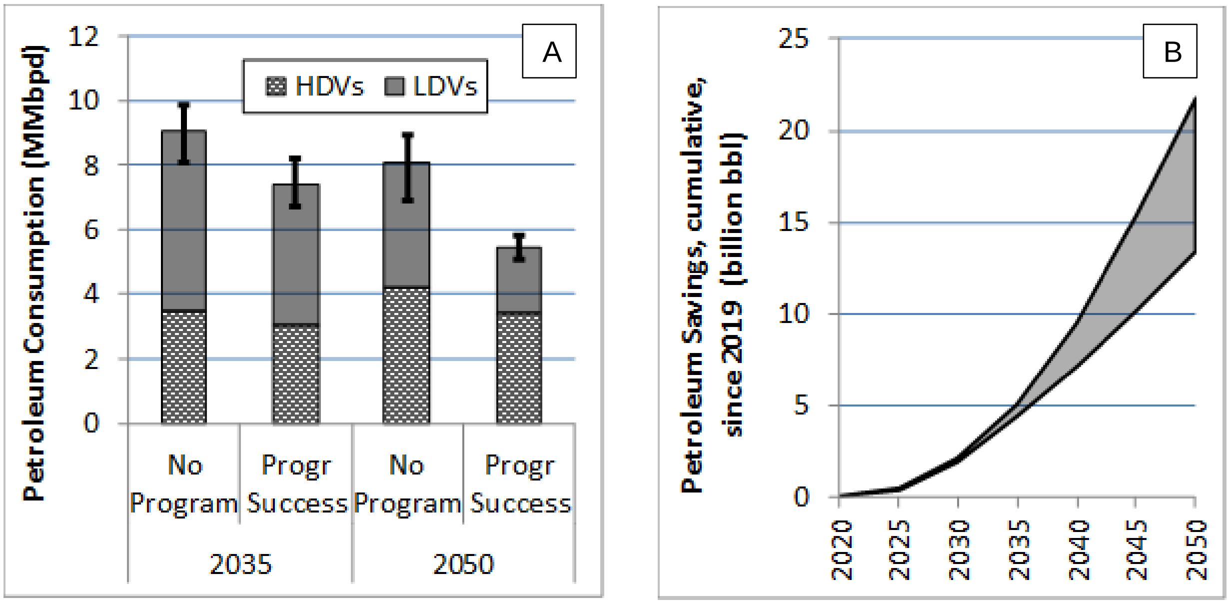

Figure III.1.1 - Projected on-road petroleum consumption and savings
(A) Petroleum consumption under the No Program and Program Success cases in 2035 and 2050; (B) range of cumulative petroleum savings attributed to all VTO and FCTO technology programs as estimated using four LDV consumer choice models (from Stephens et al., 2017)

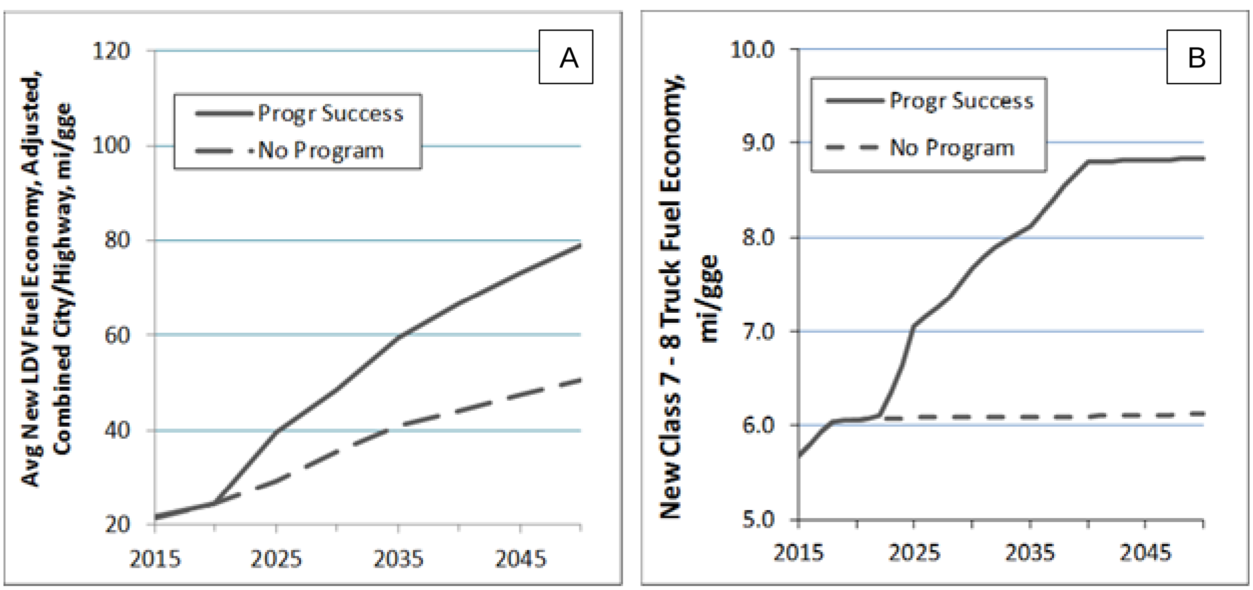

Figure III.1.2 - Fleet-averaged fuel efficiency through 2050 for the program success and no program cases (A) light-duty, and (B) class 7–8 combination unit (heavy-duty) trucks (from Stephens et al., 2017)]

Projections of LDV adoption indicate that the fuel savings from advanced vehicle technologies offset the upfront cost, resulting in a net reduction of consumer cost. In 2035, the projected decrease in annual fuel expenditures for LDVs ranges from $62 billion to $85 billion (2015$), while the projected increase in new LDV expenditures in the same year ranges from $3 billion to $21 billion (2015$), as shown in Figure III.1.3. In addition, investments in technology for HDVs result in projected fuel savings of $24 billion, while vehicle costs increase by $3 billion. By 2050, annual fuel cost savings for LD and HD vehicles reach $156 billion to

$246 billion, while vehicle purchases are projected to be $30 billion to $35 billion more expensive. Ranges in costs and savings for LDVs represent the results of using multiple vehicle choice models to estimate the vehicle fleet.

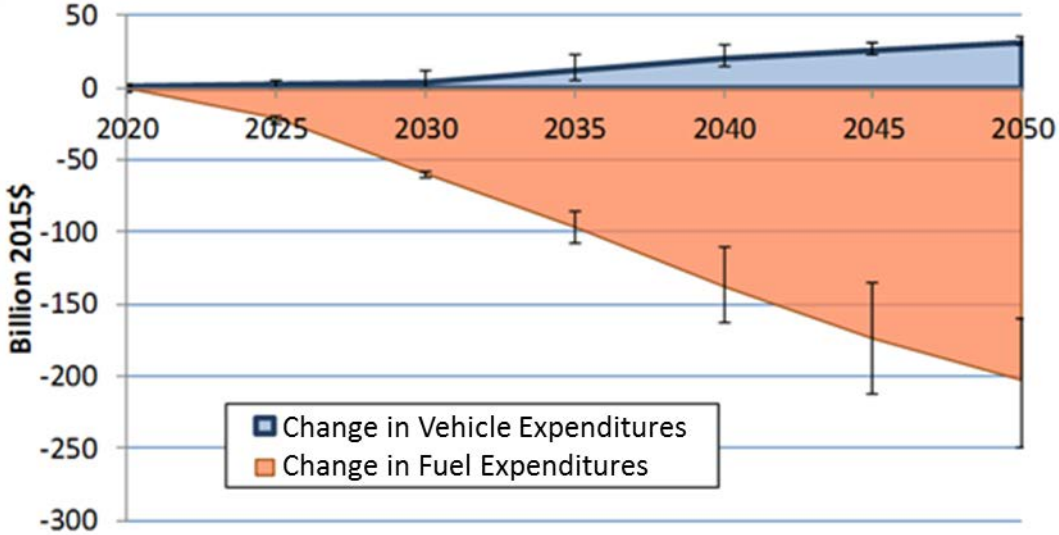

Figure III.1.3 - Difference in annual national consumer costs of vehicle purchases and fuel costs for on-road vehicles through 2050 between the No Program and Program Success Cases (from Stephens et al., 2017)

Benefits were disaggregated by individual program technology areas, which included the FCTO program and the VTO research and development (R&D) programs of Electrification, Advanced Combustion Engines and Fuels, and Materials Technology. Benefits of MD and HD vehicles were attributed to Advanced Combustion Engines and Fuels, the program which funds most of the HD technologies. Table III.1.1 presents the ranges of projected petroleum savings and emissions reductions attributed to these programs. The estimated savings depend on market penetration projections that assume that technologies that are closer to commercialization will ramp up more quickly than those that are in earlier stages of development such as fuel cells and hydrogen infrastructure.

Table III.1.1 - Projected Ranges of Petroleum Savings and Emissions Reductions in 2025, 2035, and 2050 by VTO and FCTO Technology Programs

	Annual Petroleum Savings (million bpd)				Annual Emissions Reduction (million tons CO_{2e})		
Program Area	2025	2035	2050		2025	2035	2050
Electrification	0.03–0.19	0.28–0.61	0.34–1.44		5–29	57–123	74–272
Advanced Combustion Engines and Fuels	0.25–0.32	0.66–1.01	0.85–1.01		47–62	122–194	151–182
Materials Technology	0.02–0.03	0.06–0.12	0.06–0.08		4–7	11–24	11–15
Hydrogen Fuel Cells	0.00–0.05	0.11–0.45	0.35–0.96		0–6	14–46	59–148

As shown in Table III.1.2, the Program Success case projects a lower total fuel use relative to the No Program case. Program Success is estimated to reduce cumulative petroleum consumption by LD, MD, and HD vehicles by 13.4 to 21.7 billion barrels between 2019 and 2050, a decrease of 13% to 19% of cumulative consumption compared to the No Program case. The fuel economy improvements shown in Table III.1.2 are large, with adjusted, combined city/highway fuel economy of new LDVs potentially increasing by as much as 62% by 2035 (compared to the No Program case). Projections of expenditures on fuel and vehicles indicate that the fuel savings from advanced technology vehicles are likely more than twice the increase in expenditures on new vehicles, as shown in Table III.1.2.

Table III.1.2 - Projected Benefits of VTO and FCTO R&D Technology Programs

Metric	2025	2035	2050	2050
Oil savings, cumulative (billion barrel)[a]				
Light-duty Vehicles	0.3–0.4	1.6–1.8	3.4–4.1	9.0–17.3
Medium- and Heavy-duty Vehicles	0.04	0.3	0.9	4.4
Total	0.4–0.5	1.9–2.2	4.4–5.0	13.4–21.7
Oil savings, rate (million bpd)[a]				
Light-duty Vehicles	0.4	0.8–1.0	0.9–1.5	1.0–2.7
Medium- and Heavy-duty Vehicles	0.06	0.2	0.4	0.8
Total	0.4–0.5	1.1–1.2	1.3–1.9	1.8–3.5
New vehicle mpg improvement (percent)[b]				
Light-duty Vehicles	32–48%	36–48%	36–66%	43–77%
Medium- and Heavy-duty Vehicles	12%	19%	24%	28%
On-road stock mpg improvement (percent)[b]				
Light-duty Vehicles	6–7%	16–18%	24–30%	38–68%
Medium- and Heavy-duty Vehicles	2%	7%	13%	23%
Reduction in annual fuel expenditures (billion 2015$/yr)[a]				
Light-duty Vehicles	15–21	44–49	62–85	94–184
Medium- and Heavy-duty Vehicles	3	12	24	63
Total	18–24	56–61	85–108	156–246
Increase in annual expenditures for new vehicle purchases (billion 2015$/yr)[a]				
Light-duty Vehicles	−2–+3	−3–+10	3–21	27–32
Medium- and Heavy-duty Vehicles	1	2	3	3

Total	−1–+4	−1–+12	6–24	30–35
a “Reductions” and “savings” were calculated as the difference between the results from the Program Success case (i.e., in which requested DOE funding for this technology is received and the program is successful) and the results from the baseline (No Program) case (i.e., in which there is no future DOE funding for this technology). Negative reduction values reflect increases. All cumulative metrics are based on results beginning in 2019.				
b Improvement relative to baseline (No Program) fleet in the same year.				
c AEO 2016 only projects through 2040; thus oil security savings are not available for 2050.				

Conclusions

Analysis of Program Success and No Program scenarios indicate that, as a result of the combined success of VTO and FCTO technology programs, the average fuel economy of the on-road LDV stock could be 24% to 30% higher by 2035 compared to the No Program case, and by 2050, the increase could be 39 to 68%. The increase in the average fuel economy of on-road stock of MD and HD vehicles could be 23% higher than in the No Program case by 2050. The resulting petroleum savings were estimated to be as high as 1.9 million bpd in 2035 and up to 3.5 million bpd in 2050. Projections of advanced-technology vehicles indicate that, although advanced-technology vehicles may be more expensive to purchase, the fuel savings result in a net reduction of consumer cost. In 2035, reductions in annual fuel expenditures are projected to range from $85–$108 billion, while the projected increase in new vehicle expenditures in the same year ranges from $6–$24 billion (both in 2015$).

Uncertainties in these estimates arise from uncertainties in market penetration by advanced vehicle technologies in LDVs. Ranges of estimated benefits are presented to show the magnitude of this uncertainty.

The resulting benefits to the United States will increase affordability of transportation through fuel savings, increase national security through reduced dependence on petroleum, and support economic growth through energy exports, innovation, and environmental mitigation savings.

Key Publications

Stephens, T.S., A. Birky, and D, Gohlke. Vehicle Technologies and Fuel Cell Technologies Office Research and Development Programs: Prospective Benefits Assessment Report for Fiscal Year 2018. Argonne National Laboratory, Argonne, IL, report ANL/ESD-17/22, November, https://www.osti.gov/scitech/biblio/1410412-vehicle-technologies-fuel-cell-technologies-office-research-development-programs-prospective-benefits-assessment-report-fiscal-year, accessed December 14, 2017.

III.2 Integration of BEAM and PLEXOS Modeling Frameworks

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Project Introduction

Increased adoption of PEVs can offer benefits of reduced energy and petroleum consumption, increased energy diversity, reliability, and security, and operational cost savings for the electricity system, depending on the way they are used and the way they charge. PEV charging can either be left unmanaged, such that drivers charge their vehicles based on their own mobility needs and preferences, or charging can be managed directly or indirectly. While there is a spectrum of approaches, smart charging generally means the utility or some other centralized entity has direct control over the timing of active PEV charging when it is plugged in. Alternatively, drivers may pre-program their PEV in response to electric rate incentives to only start charging during off-peak times.

Prior studies have largely ignored driver behavior and have not produced realistic estimates of smart charging or off-peak charging programs and their impacts, because these studies typically oversimplify PEV mobility and infrastructure availability. A more accurate estimate of achievable benefits from different PEV charging strategies is useful for informing the development of smart charging programs, which are still primarily in pilot stages of implementation.

This project integrates the results from a detailed agent-based vehicle model, BEAM, with a grid model, PLEXOS®, which represents the unit commitment and economic dispatch of generators. Our initial focus is on the California electricity grid, which has a goal to have half of its electricity generated from renewable sources by 2030, and which projects to have about two million PEVs around that time.

Objectives

Our objectives for this project are the following:

- Link BEAM with the PLEXOS® production cost model of the grid to enable simulations of the impacts of the electrified transportation system on the power system.
- Develop a method for representing mobility and infrastructure constraints of PEV charging from BEAM as a load-shifting resource in PLEXOS®, while still maintaining convenience of PEV drivers.
- Compare the differential impacts, in terms of grid operating cost and renewable energy utilization and curtailment, of unmanaged, smart and off-peak PEV charging strategies.
- Evaluate the economic impacts on the grid of different levels of PEV adoption, and the capacity and limit of the grid to absorb increased PEV charging loads.

Approach

We develop the following approach to couple the BEAM model to the PLEXOS® production cost model to achieve a highly-detailed simulation of PEV mobility, spatiotemporal charging demand, load flexibility, and the California electricity market.

1. *BEAM Model: PEV Mobility/Charging.*
   BEAM is an agent-based model of PEV mobility and charging behavior, designed as an extension to the Multi-Agent Transportation Simulation model. BEAM simulates PEV mobility and charging behavior for three representative weekdays for about 68,000 PEVs in the San Francisco Bay Area. Charging sessions (defined by the period of time the PEV is plugged in) are simulated as unmanaged, but the time between the end of active charging and the actual unplug event concluding the session is tracked for later use and exported as an input into the next step.

2. *Charging Load and Flexibility Constraint Aggregation.*
   We aggregate simulated charging sessions from BEAM into a set of PEV smart charging load profiles and associated constraints, scaled to a statewide forecast projected for the year 2025 by the California Energy Commission. The charging session data are aggregated by PEV type into both an unmanaged trajectory of delivered energy (when the vehicle charges immediately and at full power when it plugs in), and an alternate trajectory that represents delaying charging to the maximum extent possible while still delivering the same amount of energy by the end of the session. These trajectories are treated as maximum and minimum constraints that bound possible dispatch of smart charging loads, and still ensure the same end state of charge of the PEV as with unmanaged charging. Corresponding power constraints on charging are also produced based on the number of connected vehicles in each hour. Time-of-use (TOU) charging is represented as the shifting of PEV charging sessions to begin at staggered overnight times between 10 p.m. and 2 a.m. In order to capture the realistic behavior of an average day, the data from charging sessions from the second day of a three-day BEAM run of representative weekdays are used for the constraint aggregation. A full week of data, constructed by calibrating to observed charging data, is then repeated to create an annual data set.

3. *Load and Constraint Scaling to California Vehicle Adoption Forecasts.*
   The aggregated smart charging constraints and unmanaged and TOU loads produced from BEAM in Step 2, based on PEVs in the San Francisco Bay Area, are scaled from magnitudes that represent the San Francisco Bay Area PEV stock in 2017 to that of the whole state of California in 2025. The scaling occurs in two parts, from the Bay Area to each utility zone in California based on respective BEV and PHEV vehicle stock as of 2017, and then from 2017 to California in 2025 based on a California Energy Commission forecasted 2025 adoption level ranging from 0.95 million to 2.5 million PEVs in the state. We assume that current trends in PEV sales will continue, and that 60%of the 2025 adoption level will be met by BEVs, and 40% by PHEVs.

4. *PLEXOS® Power Sector Model.*
   We pass this data to PLEXOS®, where we use the most recent publicly available zonal database constructed by the California Independent System Operator (CAISO) for the state's 2014 Long-Term Procurement Planning process. We run the PLEXOS® simulation deterministically for four scenarios in 2025, and assume that California meets its 50% renewable energy requirement: a case with no PEVs, a case with all unmanaged PEVs, a case with all smart charging PEVs, and a case with PEVs charging during overnight off-peak TOU periods. We export as results the total system cost, electricity prices, renewable curtailment and generation, and charging behavior.

Results

We find that integrating PEVs in an unmanaged charging scenario compared to a smart charging and TOU charging scenario has the following system impacts for California's grid in terms of total system cost and renewable energy curtailment:

- The total system operating cost, including the net costs of electricity imports and exports, rises by about $601 million/year in California with the addition of 2.5 million unmanaged PEVs, whereas the cost increase is just $298 million/year with smart charging PEVs. Therefore, about $304 million in costs per year are avoided by smart charging. With 2.5 million PEVs charging according to TOU off-peak rate schedules, $245 million in system costs per year are avoided. Because the analysis holds generation and transmission infrastructure as constant, these costs reflect the wholesale operating costs to generate energy and do not include capital costs, transmission and distribution costs, and any other additions that comprise retail electricity rates for customers. The system costs at the three different PEV adoption levels, with the different charging strategies, are shown in Figure III.2.1 below.

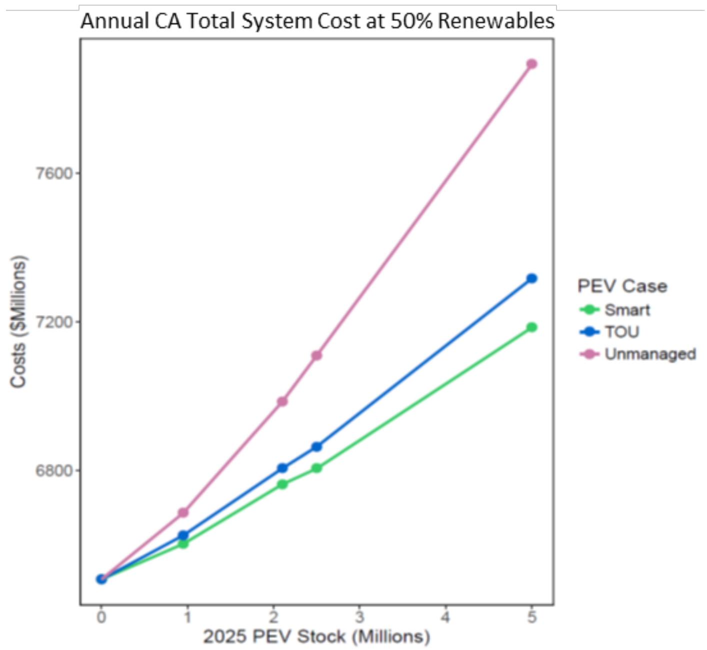

Figure III.2.1 - Annual California Total System Cost

- With 50% of California's energy consumption met by renewable energy, in the absence of smart charging of PEVs, we find numerous instances of renewable curtailment over the course of 2025. With 2.5 million PEVs, renewable curtailment decreases by about 300 GWh per year with smart charging, which is a reduction of 27% of total curtailment compared to the case when the 2.5 million PEVs are unmanaged. The curtailment at the three different PEV adoption levels, with the different charging strategies, is shown in Figure III.2.2 below.

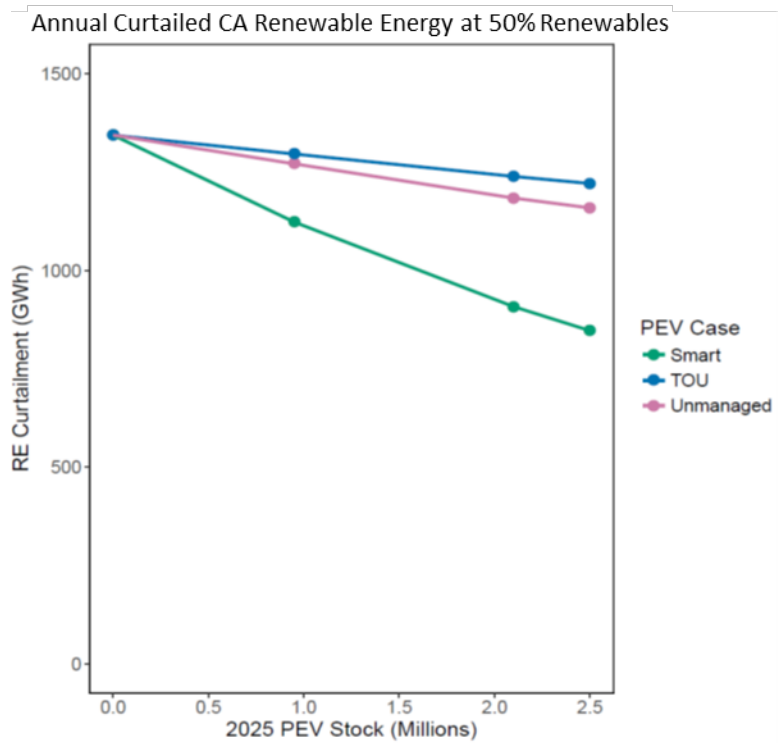

Figure III.2.2 - Annual Curtailed California Renewable Energy

Conclusions

In FY 2017, we have successfully linked the BEAM simulation model with PLEXOS®. In this linkage, we have represented the mobility constraints of PEV drivers and have evaluated the economic and grid impacts of different types of PEV charging strategies, and different levels of PEVs using California as an initial case study of a grid with high renewable energy penetration. This information will help key stakeholders sure future transportation technology takes economic growth, national security, and reliability into consideration.

Key Publications

Szinai, Julia K., Sheppard, Colin J.R., Abhyankar, Nikit, Gopal, Anand R. "Managing electric vehicle charging can reduce renewable energy curtailment and the cost of grid operations." January 2018. *In review at Applied Energy*.

III.3 Applied Analysis of Connected and Automated Vehicle Technologies

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Project Introduction

The potential impacts of connected and automated vehicles (CAVs) on transportation energy use are large and highly uncertain. The rapid advancement of CAV technologies may disrupt vehicle use, ownership, and design, resulting in large changes in energy consumption, use of alternative transportation modes, and development and adoption of efficiency-improving vehicle technologies. A review and synthesis of existing literature and identification of high-priority knowledge gaps and research questions were needed to assist DOE in planning research and analysis relevant to the energy and petroleum consumption of CAVs and associated implications for national security and economic growth.

Objectives

To help identify analysis and research needs related to CAVs, this project has the following objectives:

- Review recent literature related to CAVs
- Provide a framework that synthesizes analysis and simulation case studies of potential CAV adoption scenarios
- Identify key knowledge gaps and uncertainties for assessing CAV energy impacts, emphasizing research and analysis priorities to better understand these impacts.

Under a related effort, methods are being developed to address these gaps to enable estimation of potential energy impacts of CAVs at a national level.

Approach

In order to establish bounds on potential energy use impacts by future CAVs and to identify the key knowledge gaps, relevant studies were reviewed. From these, the state of knowledge of potential energy and market implications of CAVs for passenger travel energy use were assessed, and information on consumer costs affected by CAVs was reviewed. Based on this review, lower and upper bounds on CAVs energy use by LD passenger vehicles in the United States were estimated, and key uncertainties/knowledge gaps were identified.

Ranges of energy impacts for various CAVs features and applications were obtained from the literature reviewed. From these, ranges of potential CAV effects on VMT and vehicle efficiency were estimated and combined to evaluate impact ranges for national LDV fuel use, and for CAV technology costs to consumers. In order to bound potential ranges of impacts, this assessment assumed complete CAV adoption under several distinct scenarios. These include a baseline scenario to represent fuel use by the current U.S. LDV fleet and three CAV scenarios differentiated by automation, connectivity level, and assumed level of ridesharing.

The automation level distinctions within the CAV scenarios included partial automation, such as driver assistance technologies that still require an attentive driver to control the vehicle, and full automation, including driverless vehicles. The fully connected and automated scenarios were further subdivided into two: with and without ridesharing. The four selected scenarios (including the baseline) were named to indicate the assumed level of automation and whether or not ridesharing is included, as follows:

1. “Conventional,” the base case of current conventional (without automation or connectivity) privately owned vehicles
2. “Partial,” partially automated and connected, privately owned vehicles
3. “Full-No Rideshare,” fully automated and connected vehicles with no ridesharing
4. “Full-With Rideshare,” fully automated and connected vehicles with ridesharing.

Ranges of factors for various CAVs technologies and assumptions made in developing scenarios and estimated bounds for the energy impacts of factors are documented in Stephens et al. (2016).

Sources providing estimated impacts of CAVs technologies on cost of vehicle ownership and travel costs were also reviewed. These costs included vehicle purchase and ownership costs, as well as value of time spent traveling.

Results

Bounds on energy impacts of CAVs for passenger travel were estimated based on a review of literature (Stephens et al, 2016). Consumer costs impacted by CAVs were also reviewed. Energy use bounds were estimated based on combined effects on travel demand (VMT) and vehicle efficiency. The VMT impact calculations included vehicle occupancy assumptions to translate between person miles traveled and VMT. The efficiency calculations relied on literature-reported values for different CAV feature impacts on fuel consumption rates (e.g., due to vehicle-to-infrastructure communication/coordination, vehicle platooning, etc.), and also included a first-order disaggregation of each feature’s impact in different driving situations (i.e., city vs. highway driving, and travel at peak vs. off-peak times). The relative impacts were then weighted by the amount of driving that takes place in those different situations.

Estimated impacts were synthesized into three CAVs scenarios: Partial (partial automation with some connectivity), Full-No Rideshare (full automation with high connectivity without ridesharing), and Full-With Rideshare: (full automation with high connectivity with ridesharing). Partial automation was assumed to include technologies such as driver assistance that still require an attentive driver to control the vehicle, corresponding to SAE levels 1 or 2 [1], with limited connectivity. Full automation was assumed to correspond to SAE Levels 4 and 5, allowing vehicle operation without an attentive driver (or even without a person in the vehicle), and with connectivity permitting communication between travelers, vehicles, traffic control devices, and traffic control centers. Ridesharing refers to a net increase in vehicle occupancy resulting from two or more people riding together in a vehicle during some or all of their travel.

The upper bound estimates for each scenario assume combinations of CAV effects on VMT and vehicle efficiency that result in maximal energy increase (i.e., many more miles traveled with little or no fuel economy gains), whereas the lower bound estimates assume the reverse (i.e., minimal increases in VMT combined with more aggressive vehicle efficiency improvements). The results, summarized in Figure III.3.1, illustrate wide separation between the scenarios' upper and lower bounds on U.S. LDV fuel use, reflecting the large uncertainties in CAVs' impacts on both vehicle fuel consumption rates and VMT. The upper bound for the Full-No Rideshare scenario represents the highest increasing fuel use case with triple the annual fuel use of the base scenario. The lower bound of the "Full-With Rideshare" scenario represents the lowest decreasing fuel use case with less than 40% of the base scenario's fuel use. In contrast, the partial automation scenario shows a much more modest range of impacts, on the order of ±10% for the upper and lower bounds relative to the base scenario.

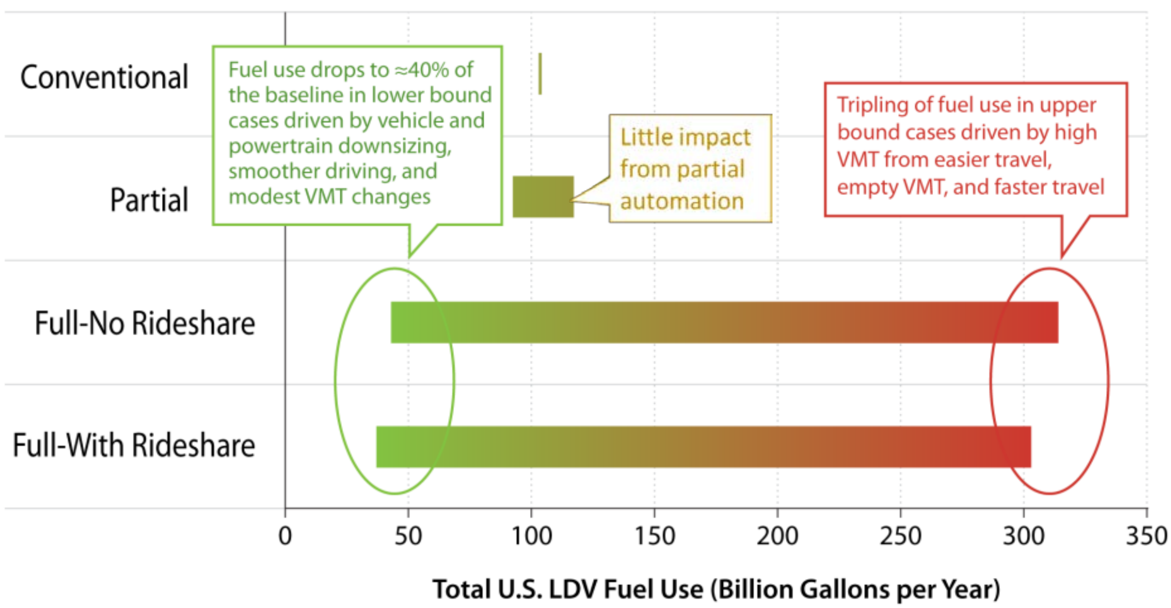

Figure III.3.1 - Estimated bounds on total U.S. LDV fuel use per year under the base (Conventional) and three CAV scenarios.
Based on the study's synthesis approach from CAV feature impact ranges reported in reviewed literature (from Stephens et al., 2016).

Figure III.3.1 also highlights the most important factors influencing the upper and lower bounds on fuel use. For the upper bound cases, large VMT changes due to easier travel (faster travel and reduced travel time cost) serve as the largest driver on increasing fuel consumption, with empty travel by driverless CAVs and increased fuel consumption per mile due to high-speed travel representing the next most influential factors. In the lower bound scenarios, decreased fuel use is largely due to aggressive vehicle and powertrain downsizing, combined with smoother driving and only modest VMT increases (which can be further offset by ridesharing).

Several potential factors influencing vehicle efficiency were identified in the CAVs literature that were considered here, including: vehicle right-sizing, smoother driving, platooning, faster (safe) travel, collision avoidance (resulting is less congestion), and intersection vehicle-to-infrastructure connectivity. The potential ranges of the effects of these factors on fuel consumption per mile were estimated for each of the four scenarios as shown in Figure III.3.2. Right-sizing (under a wide range assumed for the potential reduction of vehicle mass) gives the largest potential efficiency increase. Improved driving efficiency from smoother driving, platooning, and connectivity offer potential reductions in fuel consumption as well. Faster (safe) travel can potentially increase fuel consumption.

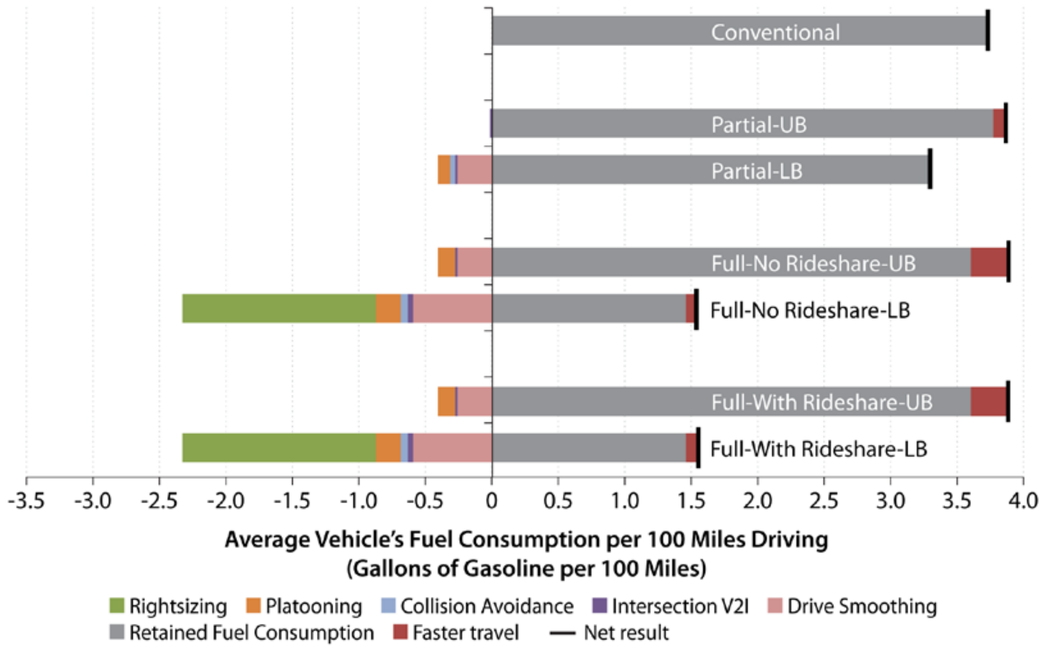

Figure III.3.2 - Estimated bounds on vehicle fuel consumption rate for each scenario (gallons of gasoline per 100 miles of driving) (from Stephens et al., 2016)

Factors that potentially influence travel demand by LDVs (as indicated by VMT) included easier travel (lower perceived cost of travel time), increased travel by currently underserved persons, empty VMT (by driverless vehicles being repositioned), changes in ridesharing, and shifts from other travel models to CAVs. Ranges estimated from literature sources for each of these factors in the four scenarios are shown in Figure III.3.3. As can be seen, easier travel can potentially increase travel demand by a large amount. Increased travel by underserved and empty miles traveled may be significant, while ridesharing and mode shift were estimated to be less significant.

Figure III.3.4 illustrates the resulting upper and lower bounds on total costs per passenger mile for each scenario. Most of the CAVs cases show substantial decreases in costs to consumers—for the lower end assumptions in the Full-With Rideshare scenario, the net cost reduction relative to the baseline is roughly 60%. Note that the significant reductions in estimated consumer costs are driven largely by reductions in travelers' perceived travel time costs, which, in addition to being highly influential, is a highly uncertain factor.

The wide range between the lower and upper bounds on future vehicle energy use reflects the large uncertainties in ways that CAVs can potentially influence vehicle efficiency and use through changes in vehicle design, driving, and travel behavior. In addition, future CAV technology adoption rates are very uncertain. Use of alternative powertrain technologies, such as electric drive, is likely to reduce both the upper and lower bounds on fuel consumption for the examined scenarios. However, the relative impact of different CAV features in advanced powertrains is expected to differ from that in conventional vehicles. Therefore, future work will explore the combined impacts of advanced powertrain and CAV technologies.

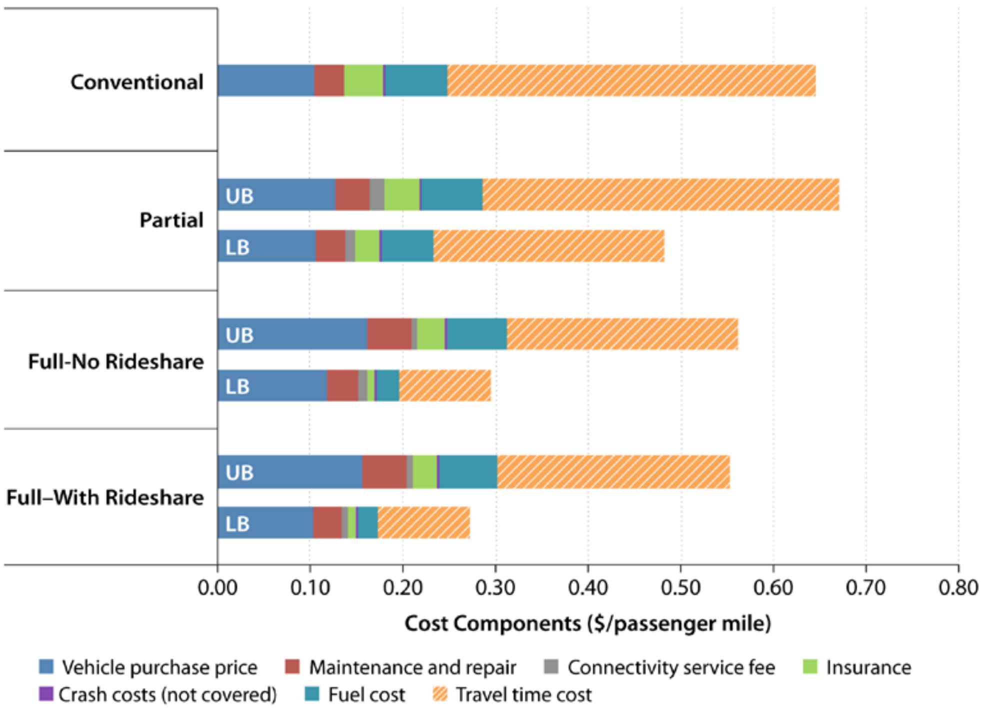

Figure III.3.3 - Potential national LDV VMT under the "Conventional" and CAV scenarios (from Stephens et al., 2016)

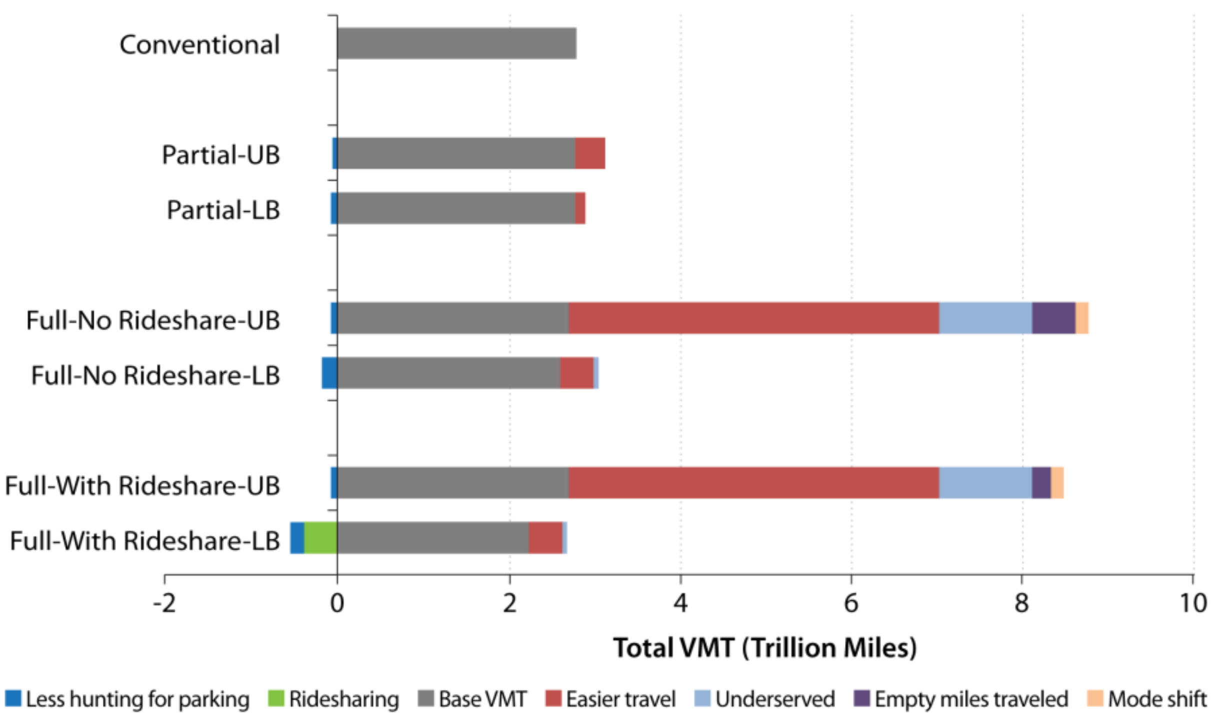

Figure III.3.4 - Estimated bounds on consumer cost components under the Conventional and selected CAV scenarios (from Stephens et al., 2016)

For each of the factors examined in this report, the most significant drivers of possible fuel use changes have been identified. Based on these, the most important knowledge gaps in each of these factors was also assessed and prioritized. The highest-priority uncertainties and knowledge gaps include:

- Potential impacts of advanced CAV technologies on travel demand
- Potential adoption levels of advanced CAV technologies
- Potential impacts of advanced CAV technologies on vehicle fuel efficiency
- Potential impacts of advanced CAV technologies on vehicle redesign/resizing
- Potential energy impacts of HD CAV technologies.

In the report documenting the energy bounds and knowledge gap assessment, each of these five areas is discussed in more detail, with key research questions, data gaps, and possible approaches to addressing these questions (Stephens et al, 2016).

Conclusions

The range of potential impacts of CAVs on energy use by the U.S. transportation sector is large and highly uncertain. Upper and lower bounds of these energy impacts were estimated from a synthesis of recent studies and available data. Generally, the factors 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 here, vehicle/powertrain resizing offers 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 CAV factors considered can potentially decrease fuel consumption per mile with the exception of higher speed travel. Note that an increase in fuel consumption due to larger CAVs was not considered since that was not mentioned in the literature reviewed. However, an increase in average vehicle size associated with CAVs could be possible.

The potential influence of CAVs on travel demand is quite large, and possible increases due to easier travel is the largest component. Repositioning of empty CAVs could increase VMT, but few estimates of this increase were found in literature, and these estimates were small (a few percent). Increased ridesharing 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. Prices are decreasing rapidly with technology development, and are expected to decrease much more if produced in large volumes. However, consumer attitudes and preferences for CAVs are not well understood, and require further research.

Important areas requiring significant research and analysis to reduce uncertainties include: assessing potential changes in travel demand due to CAVs, estimating future CAV adoption, analyzing potential effects on vehicle efficiency and redesign, and estimating future HD CAV energy impacts.

Key Publications

Stephens T.S., J. Gonder, Y. Chen, Z. Lin, C., C. Liu, and D. Gohlke (2016) "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles," National Renewable Energy Laboratory Technical Report NREL/TP-5400-67216, http://www.nrel.gov/docs/fy17osti/67216.pdf.

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1. SAE International. 2016. “Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles,” Recommended Practice J3016_201609, revised September 30. Accessed December 14, 2017. http://standards.sae.org/j3016_201609/.

III.4 Charging Electric Vehicles in Smart Cities: An EVI-Pro Analysis of Columbus, Ohio

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Total Project Cost: $300,000 DOE share: $300,000 Non-DOE share: $0

Project Introduction

PHEVs and BEVs, collectively known as PEVs, provide various benefits to the United States. They reduce energy consumption and reliance on petroleum, which accounts for over 90% of total U.S. transportation energy consumption [1] and is characterized by an extremely volatile market. Substituting electricity for gasoline and diesel could significantly improve U.S. energy security, providing greater fuel diversity in a market currently dominated by a single energy source.

PEV sales in the United States increased by 40% in 2016, reaching a total stock of over 500,000 vehicles [2]. Still, widespread market adoption of PEVs remains hindered by many factors, including limited availability of models and styles, higher cost compared with conventional vehicles, and the lack of a convenient and ubiquitous network of charging stations. It is particularly important to understand the barriers to and benefits of developing a widespread and effective network of PEV charging stations, also known as electric vehicle supply equipment (EVSE). Such a network would promote PEV consumer acceptance and market growth, enable long-distance travel for BEVs (alleviating the range anxiety concerns of many consumers), and potentially increase the share of electric miles driven by PHEVs. Infrastructure planning must anticipate PEV adoption while remaining cost-effective so low station utilization does not severely undermine the business case for building and operating stations [3]. Sufficient revenue is required to build and continue operating the EVSE network as the PEV market grows over time.

This project presents an approach for developing a U.S. network of non-residential EVSE that enables broader PEV adoption and maximizes PEV use. This analysis can help inform various public and private stakeholders who are seeking to provide nationwide charging coverage and improve the business case for building stations by maximizing station utilization.

Objectives

This project addresses the fundamental question of how much charging infrastructure is needed in the United States to support PEVs. It complements ongoing EVSE initiatives by providing a comprehensive analysis of national PEV charging infrastructure requirements. The result is a quantitative estimate for a U.S. network of non-residential (public and workplace) EVSE that would be needed to support broader PEV adoption. The analysis provides guidance to public and private stakeholders who are seeking to provide nationwide charging coverage, improve the EVSE business case by maximizing station utilization, and promote effective use of private/public infrastructure investments.

This PEV charging study complements the existing literature by providing updated and comprehensive analysis of the national PEV charging infrastructure requirements within cities, towns, and rural areas and along corridors connecting them. Additionally, a case study of U.S. DOT Smart City Challenge Award Winner Columbus, Ohio is conducted to provide a local perspective. This work provides guidance to regional and national stakeholders on non-residential EVSE strategies and plans, both to reduce range anxiety as a barrier to increased PEV sales, and to promote effective use of private/public infrastructure investments.

Approach

PEV charging infrastructure requirements—the number of stations and plugs required to provide a convenient and ubiquitous network of PEV charging opportunities—will evolve as PEV adoption increases. In particular, two driving forces characterize the charging infrastructure required to support a growing fleet of PEVs:

1. A basic level of geographic coverage is required to guarantee nationwide charging opportunities and enable long-distance travel for BEVs.

2. Over time, a larger network of stations will be required to satisfy growing charging demand, increasing non-linearly with PEV market share.

Figure III.4.1 illustrates coverage (blue line) and demand (black line) infrastructure requirements for different PEV market shares. The coverage requirement is independent of PEV adoption: even if few PEVs are in use, a ubiquitous network of stations is required to enable long-distance travel, prevent range anxiety, and support PEV adoption. Therefore, a “utilization gap” exists at low PEV market shares, which is characterized by a market demand for charging infrastructure that is lower than the required coverage infrastructure; the infrastructure is underutilized, which negatively impacts station financial performance and makes it difficult to justify investment in new stations [3]. As PEV adoption increases, the demand for charging infrastructure exceeds the coverage infrastructure, creating “market pull” for the installation of additional charging stations or the addition of plugs to existing stations.

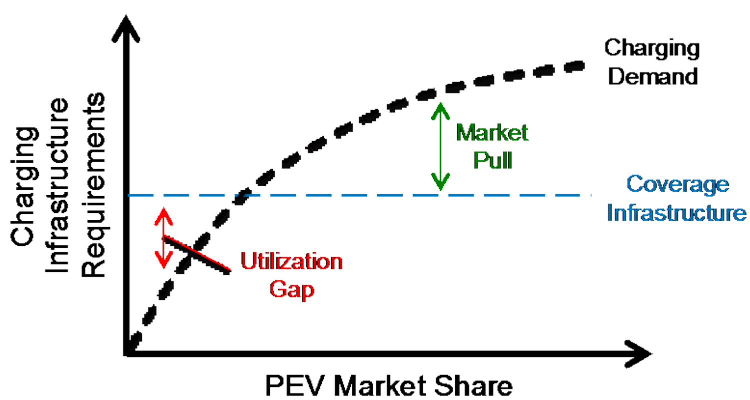

Figure III.4.1 - PEV charging requirements evolution as a function of PEV market share

The analysis is organized around the non-residential EVSE network required to meet consumer coverage expectations, and to satisfy consumer demand in high-PEV-adoption scenarios. Coverage and charging demand estimates needed to serve growing PEV markets are made for the communities where people live and the highway corridors on which they travel.

While this work is not intended to forecast future PEV markets, scenarios are developed to exercise the infrastructure estimation methodology and highlight sensitivities. The central scenario and bounds on the accompanying sensitivities have been developed using a combination of existing PEV market/technology data and engineering judgement to represent a set of scenarios that are illustrative of the role that key variables play in dictating PEV infrastructure requirements.

The analysis relies on advanced PEV simulations using NREL's Electric Vehicle Infrastructure Projection (EVI-Pro) tool run over millions of miles of real-world daily driving schedules (see Figure III.4.2 for visualization of long distance driving trips sourced from U.S. DOT). Technical considerations are made for the spatial density of PEVs concentrated in cities and towns, ambient temperature effects on electric driving range, and frequency of long distance driving days requiring non-residential EVSE.

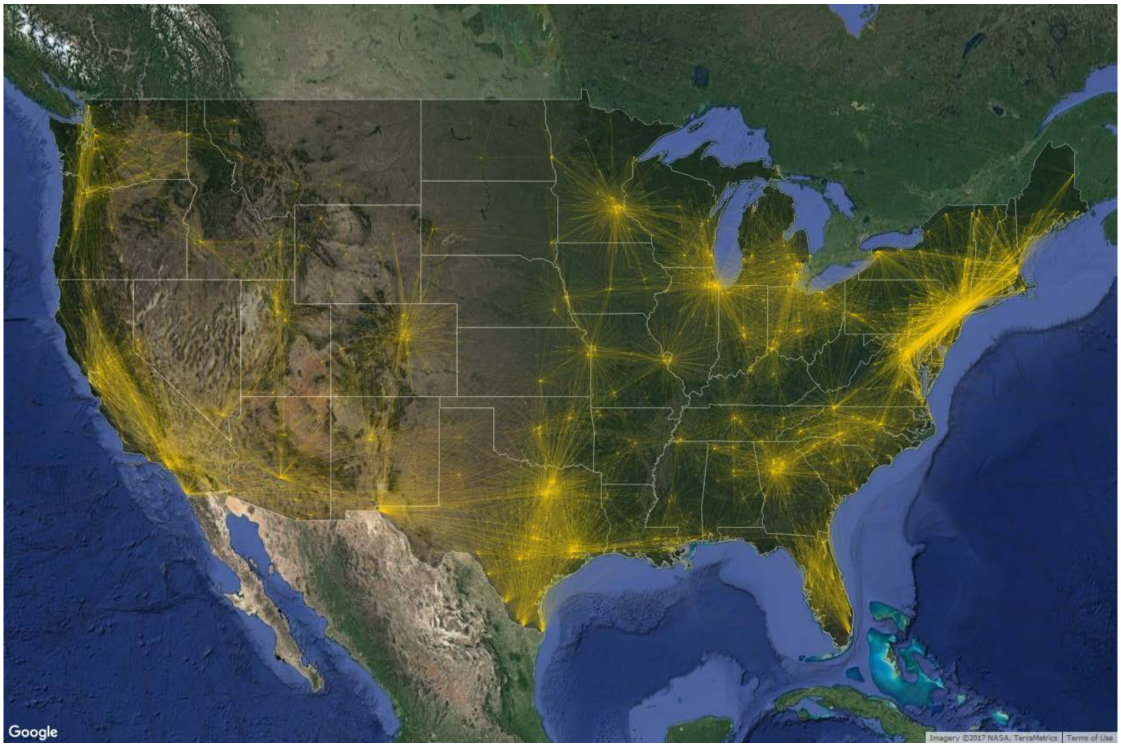

Figure III.4.2 - United States DOT long-distance auto passenger trip origin-destination pairs

Simulations are rooted in a set of foundational assumptions, which are applied across all scenarios. Consumers are simulated as performing the majority of charging at home. This assumption produces simulation results in the central scenario where 88% of PEV charging takes place at home locations (due to the large amount of time vehicles are parked at home and relatively short typical daily driving distances) consistent with early market findings in the EV Project. Charging at non-residential stations is simulated on an as-necessary basis such that consumers are able to maximize electric vehicle miles traveled (eVMT). Additionally, it is assumed that future PEVs will be driven in a manner consistent with present day gasoline vehicles (e.g., 70% of daily driving under 40 miles and 95% under 100 miles) as evidenced by data from the U.S. DOT[5] and INRIX[6].

[5] U.S. DOT Federal Highways Administration's Traveler Analysis Framework integrates data from a variety of sources to create a comprehensive set of trip tables for long distance passenger movements at the county to county level, providing person trip flows for the base year of 2008 and projections for 2040. https://www.fhwa.dot.gov/policyinformation/analysisframework/01.cfm

[6] INRIX Analytics Trips dataset provides raw anonymous GPS data points of millions of trips per day derived from industry leading geospatial data processing. http://inrix.com/products/trips/

Results

The analysis first estimates the minimum direct current fast charge (DCFC) coverage requirements for dispelling range anxiety concerns by providing a safety net of DCFC stations in cities and towns for emergency situations (such as failing to overnight charge at home). To ensure that BEV drivers in cities are never more than 3 miles from a DCFC station, approximately 4,900 DCFC stations are required across the United States. Providing the same level of coverage for towns would require approximately an additional 3,200 DCFC stations. The analysis also estimates non-residential charging plugs (work and public) required to satisfy intracommunity charging demands. In the central scenario, a total of approximately 600,000 non-residential L2 plugs and 25,000 DCFC plugs are necessary to satisfy consumer charging demand (assuming 15 million PEVs are on the road in 2030). Analysis results for the central scenario are summarized in Table III.4.1.

Table III.4.1 - Summary of Station and Plug Count Estimates for the Central Scenario (15M PEVs in 2030)

		Cities	Towns	Rural Areas	Interstate Corridors
PEVs		12,411,000	1,848,000	642,000	—
DCFC	Stations (to provide coverage)	4,900	3,200	—	400
	Plugs (to meet demand)	19,000	4,000	2,000	2,500
	Plugs per station	3.9	1.3	—	6.3
	Plugs per 1,000 PEVs	1.5	2.2	3.1	—
Non-Res L2	Plugs (to meet demand)	451,000	99,000	51,000	—
	Plugs per 1,000 PEVs	36	54	79	—

Note: Station count estimates for providing a minimum level of coverage have been omitted for community L2 stations under the assumption that non-residential L2 is primarily used for charging within walking distance of a destination (based on the low charge power and long charge time of L2 stations) and coverage for every destination was considered unrealistic for the early PEV market (however, demand estimates for L2 plug counts are included). Similarly, coverage estimates are omitted for DCFC stations in rural areas as coverage provided by stations in cities/towns and along interstate corridors was deemed sufficient.

Figure III.4.3 shows the sensitivity of total national plug requirements to several input variables. PEV electric range, commitment to maximizing PHEV eVMT, and percent of charging taking place at home have the largest effects. For instance, assuming a PEV market composed entirely of PHEV50s (PHEVs with a range of 50 miles) and BEV250s (BEVs with a range of 250 miles) (the long range preference scenario) drops non-residential L2 requirements to approximately 338,000 plugs, and public DCFC to 8,400 plugs. The sensitivity on PHEV support reveals that non-residential L2 charging is modeled almost exclusively as supporting PHEVs, where providing full support (maximizing eVMT for all PHEV owners) results in over 1,100,000 plugs, and providing no PHEV support drops the non-residential L2 plug requirement to under 63,000. Finally, the sensitivity analysis on home charging shows a decrease in the amount of charging at residential locations from 88% to 82% results in charging requirements increasing to 1,100,000 non-residential L2 EVSE plugs and over 65,000 public DCFC plugs.

Long-distance travel has been a barrier to BEV adoption due to real vehicle range limitations, which can be exacerbated by even more restrictive perceived range anxiety. Long-range BEVs have the potential to address this issue if coupled with an extensive and convenient network of DCFC stations that enable reliable intercity travel. The analysis finds that approximately 400 corridor DCFC stations (spaced 70 miles apart on average) are required to provide convenient access to BEV drivers across the U.S. Interstate System. However, corridor DCFC station count estimates range from 137 to 713 depending on network coverage and station spacing.

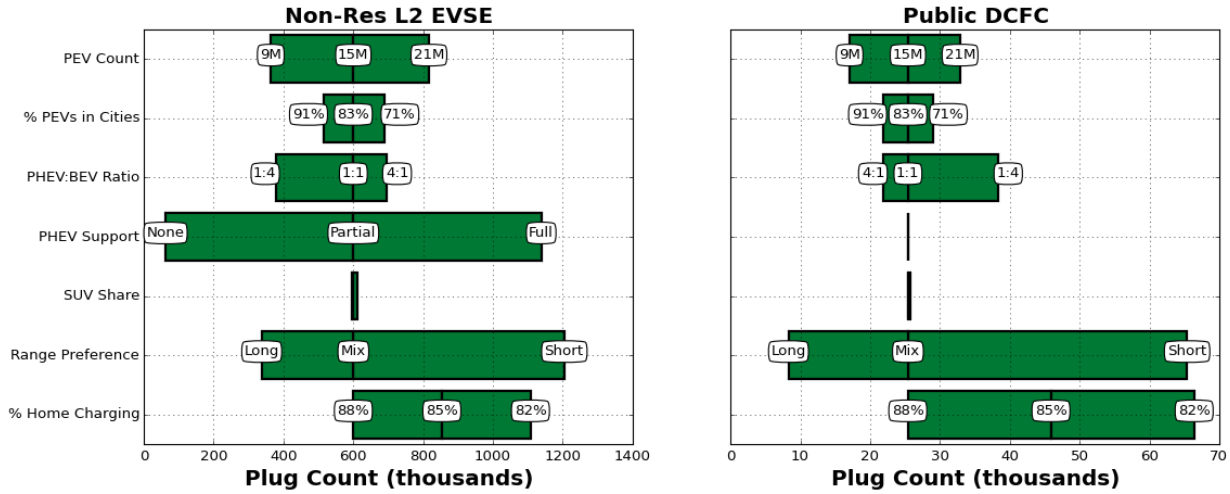

Figure III.4.3 - Effects of input variables on estimated total national plug requirements in communities

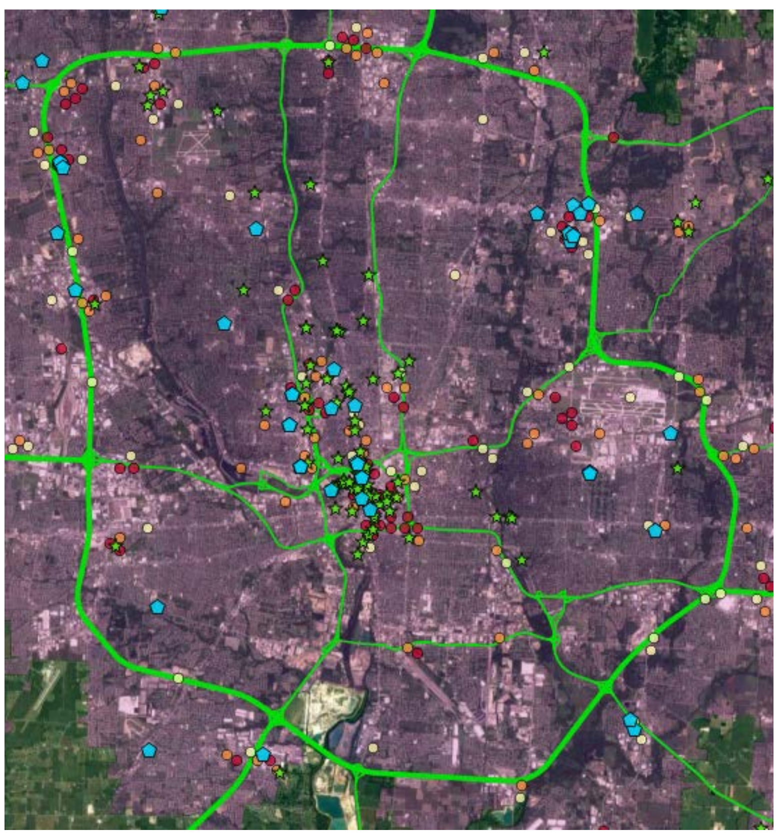
Figure III.4.4 - Simulated PEV charging “hot spots” for L2 public charging (0.3-mi diameter).

Color coded by tier (1st tier = red, 2nd tier = orange, 3rd tier = yellow), existing L2 EVSE (blue pentagons), and future sites under consideration by local planners (green stars). Purple outline denotes Columbus urban area.

Projections for Columbus-specific analysis indicate that the area would need 404 L2 plugs at multi-unit dwellings, 138 L2 plugs at workplaces, 217 L2 plugs at public locations, and 13 DCFC plugs to satisfy consumer charging demand from 5,300 PEVs in 2019. These baseline EVI-Pro results were used to conduct a spatial analysis of demand for L2 public charging in Columbus. Results from simulation of the INRIX data were processed to identify 300 "hot spots", grouped into three tiers (100 locations in each tier, color-coded by priority) based on simulated use. These results highlight locations where PEVs were simulated to be frequently parked for long durations at low battery state of charge—conditions likely to indicate future demand for non-residential L2 charging. These "hot spots" are illustrated in Figure III.4.4 as 0.3-mile-diameter bubbles, representing a walkable distance of 800 feet from the center of each bubble. These results are being used by local planners to inform the build out of EV charging in Columbus.

Conclusions

Communities are expected to have significantly larger charging infrastructure requirements than Interstate corridors under both the coverage and demand assessments. About 4,900 DCFC stations are required across cities, with an additional 3,200 DCFC stations required in towns to provide a minimum level of nationwide coverage in the communities where 81% of people live. Such a network would dampen range anxiety concerns by providing drivers with a safety net for emergency charging situations. Intracommunity charging demand analysis demonstrates how utilization of the DCFC coverage network would be expected to grow in increased PEV adoption scenarios based on a home-dominant charging assumption. Results for a 15-million PEV market estimate a DCFC plug requirement of 25,000 in communities (approximately 3.1 plugs per average DCFC station and 3.4 plugs required to support 1,000 BEVs). Demand for non-residential L2 EVSE (including work and public charging) is estimated as 600,000 plugs necessary to support 15 million PEVs (approximately 40 plugs per 1,000 PEVs).

Sensitivity analysis of the community results for consumer charging demand indicates a strong relationship between the evolution of the PEV and EVSE markets. As this analysis attempts to arrive at charging infrastructure solutions that fill the eVMT gaps between consumer travel patterns and PEV electric ranges, infrastructure requirements are not only proportional to the total number of PEVs in the system, but also inversely proportional to PEV electric range. Manufacturer and consumer preferences with respect to electric range, charging power, and utilization of residential EVSE have direct and dramatic consequences on the level of charging demand calculated in this analysis.

Results suggest that approximately 400 corridor DCFC stations are needed to enable long-distance BEV travel along Interstate highways between cities (where the majority of BEVs are likely to be concentrated). Understanding driving patterns, vehicle characteristics, and charging behavior and then prioritizing corridors and setting station spacing accordingly—as illustrated in the network scenarios—could help optimize the utility and economics of early-market corridor charging stations.

In addition to the national analysis, a detailed analysis of PEV charging requirements in the Columbus, Ohio, region was conducted to support the U.S. DOT's Smart City Challenge and Smart Columbus Initiative. Results indicate that approximately 400 L2 plugs at multi-unit dwellings and 350 L2 plugs at non-residential locations are required to support the primary Columbus PEV goal of 5,300 PEVs on the road by the end of 2019 (assuming that 12% will be adopted by multi-unit dwelling residents). Analysis finds that a minimum level of fast charging coverage across the city is required to ease consumer range anxiety concerns by providing a safety net for unexpected charging events. These results can be leveraged by similar U.S. cities as part of a strategy to accelerate PEV adoption in the LDV market.

Regardless of geographic scope, these projects suggest that organizations planning for charging infrastructure to support consumer adoption of PEVs need to be aware of the importance of consumer preferences with respect to electric range and charging behavior. Furthermore, planners should focus on providing consumers with adequate charging coverage (particularly DCFC supporting adoption of BEVs) while monitoring station utilization over time and increasing charging capacity (both in terms of rated power and number of plugs) as the PEV market continues to grow.

Key Publications

Wood, E., Rames, C., Muratori, M., Raghavan, S., Melaina, M. "National Plug-In Electric Vehicle Infrastructure Analysis" Report from the U.S. DOE Office of Energy Efficiency and Renewable Energy, September 2017, (https://www.nrel.gov/docs/fy17osti/69031.pdf)

Wood, E., Rames, C., Muratori, M., Raghavan, S., Young, S. "Charging Electric Vehicles in Smart Cities: An EVI-Pro Analysis of Columbus, Ohio" Report from the National Renewable Energy Laboratory, January 2018, (https://www.nrel.gov/docs/fy18osti/70367.pdf)

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1. U.S. Energy Information Administration (EIA) (2017). "Energy Use for Transportation." Accessed June 2017. https://www.eia.gov/energyexplained/index.cfm?page=us_energy_transportation

2. IHS Markit. (2017). "MarketInsight: Registrations and Vehicles-in-Operation." Accessed June 2017. https://www.ihs.com/products/automotive-market-data-analysis.html

3. Melaina, M.; Muratori, M.; McLaren, J.; Schwabe, P. (2017). "Investing in Alternative Fuel Infrastructure: Insights for California from Stakeholder Interviews." NREL/CP-5400-67617. Golden, CO: National Renewable Energy Laboratory. http://www.nrel.gov/docs/fy17osti/67617.pdf

III.5 VTO Baseline and Scenario

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Start Date: June 1, 2016 End Date: September 30, 2017
Total Project Cost: $350,000 DOE share: $350,000 Non-DOE share: $0

Project Introduction

Through the Office of Planning, Budget, and Analysis, EERE provides estimates of program benefits in its annual Congressional Budget Request. The Government Performance and Results Act (GPRA) of 1993 provided the basis for assessing the performance of federally funded programs. Often referred to as "GPRA Benefits Estimates," these estimates represent one piece of EERE's GPRA implementation efforts—documenting some of the economic, environmental, and security benefits (or outcomes) that result from achieving program goals.

MD and HD vehicles represent over a quarter of petroleum used in United States transportation sector. The DOE mission to improve national security and economic growth will be aided by reducing the amount of petroleum we import for transportation, which is currently 49%. To improve the estimation of VTO's impact on those applications, a large number of vehicle models were developed using Autonomie for a wide range of powertrain electrifications and component technologies. The process initially developed for LDVs was leveraged and expanded for MD and HD applications. Understanding implications of technology development will inform stakeholders to meet the DOE and VTO missions.

Objectives

- Simulate a large number of vehicle configurations, platforms, and time frames to quantify the benefits and impact of VTO technologies on component operating conditions, component sizes, vehicle energy consumption, and cost.
- Provide energy consumption and cost information to market penetration tools to quantify the fuel consumption displacement potential of VTO technologies.
- Expand the scope of the study to include MD and HD vehicles.

Approach

For LDVs, the powertrain components are sized based on a set of uniform performance criteria. For MD-HD vehicles, those criteria are very diverse and not available publicly. As a result, the vehicle technical specifications were developed from Autonomie simulation results. Thirteen class-vocation combinations were selected based on the vehicle population data from the 2002 Vehicle Inventory Use Survey, as shown in Table III.5.1.

Table III.5.1 - Selected Vehicle Classes and Vocations

Vehicle Class	Vocation/ Description
class 2b, 6000 – 10000 lbs	Small Van
class 3, 10001 – 14000 lbs	Enclosed Van
class 3, 10001 – 14000 lbs	School Bus
class 3, 10001 – 14000 lbs	Service, Utility Truck
class 4, 14001 – 16000 lbs	Walk In, Multi Stop, Step Van
class 5, 16001 – 19500 lbs	Utility, Tow Truck
class 6, 19501 – 26000 lbs	Construction, Dump Truck
class 7, 26001 – 33000 lbs	School Bus
class 8, 33001 lbs or heavier	Construction, Dump Truck
class 8, 33001 lbs or heavier	Line haul
class 8, 33001 lbs or heavier	Refuse, Garbage Pickup, Cab over type
class 8, 33001 lbs or heavier	Tractor Trailer

Six powertrain choices—conventional, integrated starter generator, HEV, extended range EV, BEV, and FCEV—were developed for these vehicle classes to understand their fuel and cost implication for each of the class-vocations considered.

This study assumes that the performance of trucks with electrified powertrains will meet or exceed those of their conventional counterpart. The parameters measured for verifying the performance capabilities are (1) 0–30 miles per hour (mph) acceleration time, (2) 0–60 mph acceleration time, (3) maximum sustainable speed at 6% grade, and (4) ability to sustain a predetermined cruising speed at highway conditions.

A baseline conventional vehicle was selected based on market share and data availability for each class-vocation combination, and its performance was estimated using simulations. The baseline models developed during this process have already been integrated into Autonomie. The summary of the main vehicle specifications and performance is shown below in Table III.5.2.

Table III.5.2 - Main Reference Vehicle Specifications and Performance

Properties	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8

		Van	Closed Van	School Bus	Service Utility	Walk In	Utility	Constr.	School bus	Transit Bus	Constr.	Line haul	Refuse	Tractor
Summary	**Baseline Engine (kW)**	130	140	187	298	149	224	150	149	243	160	336	242	261
	Test Mass (lbs)	8110	12149	13534	12083	15084	18547	23662	29385	32849	37437	71379	46306	55345
Perform.	**Cargo Mass (lb)**	1388	5898	5898	5720	7744	10340	14227	17747	4042	19934	43890	27280	31900
	Daily Driving (miles)	153	163	150	150	200	150	200	150	150	200	400	150	400
	Cruise Speed (mph)	70	70	70	70	70	65	65	60	60	60	60	60	60
	6% Grade Speed (mph)	66	49	48	70	40	65	27	33	40	28	31	28	25
	Accel Time 0-30 mph(s)	6	6.4	5.6	5.8	7.2	8.8	11.6	18.5	17.1	16.7	16.9	14.7	16.3
Trans.	**Auto / Manual**	A	A	A	A	A	A	M	M	A	M	M	M	M
	Number of gears	6	5	6	5	5	5	6	6	5	6	10	8	10
	Number of driven axles	1	1	1	1	1	1	1	1	1	1	2	1	2

The above estimate was provided to several original equipment manufacturers for comments and feedback. We have also been requesting additional information on cost share of components and sale prices of these vehicles from manufacturers. The price information will help in quantifying the ownership costs ($/mile) as we have estimated for the case of LDVs.

Based on these overall vehicle specifications and requirements, we developed and used an automated powertrain sizing process similar to the one used in LDVs to determine the appropriate component size for HEV and PEV variants.

Results

All vehicle variants were configured and sized to match or exceed the cargo carrying capacity and performance characteristics of the baseline conventional vehicle. Acceleration time (0-30 mph and 0-60 mph), grade speed (at 6%), and cruising speed were considered as the desired performance metrics. Some of these requirements determine the continuous operating requirements of components. Typically, we notice that the 6% grade requirement or the 0-30 mph acceleration time requirements are critical factors for the component sizing. HEVs and PEVs are capable of similar continuous performance as the conventional vehicle. Such a component sizing approach helps electrified vehicles easily outperform the baseline vehicles in acceleration tests. The grade speed capabilities are more evenly matched for these vehicles. The acceleration performance comparison is shown in Figure III.5.1.

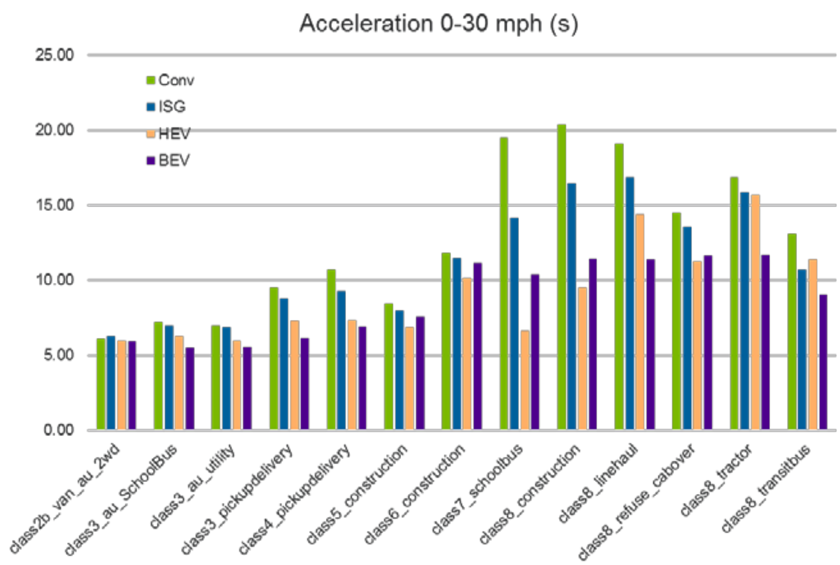

Figure III.5.1 - Electrified powertrains get better acceleration performance than the baseline vehicles

The fuel economy analysis was performed on the California Air Resources Board (ARB) transient and the EPA65 drive cycles, as both are among the regulatory cycles used by the U.S. Environmental Protection Agency. For HEVs, the fuel saving potential estimates vary from 5-10% in EPA65 to around 40% in case of ARB transient cycle, which is shown in Figures III.5.2 and III.5.3. Real world cycles are also being considered to compare to the regulatory cycles' fuel economy benefits.

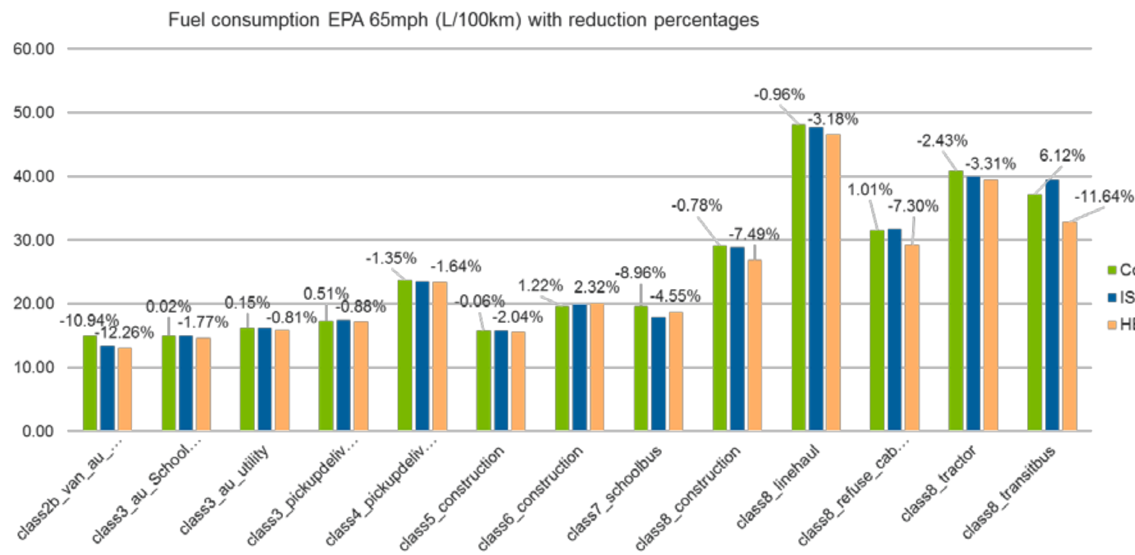

Figure III.5.2 - Fuel consumption of conventional and hybrid trucks on ARB Transient cycle

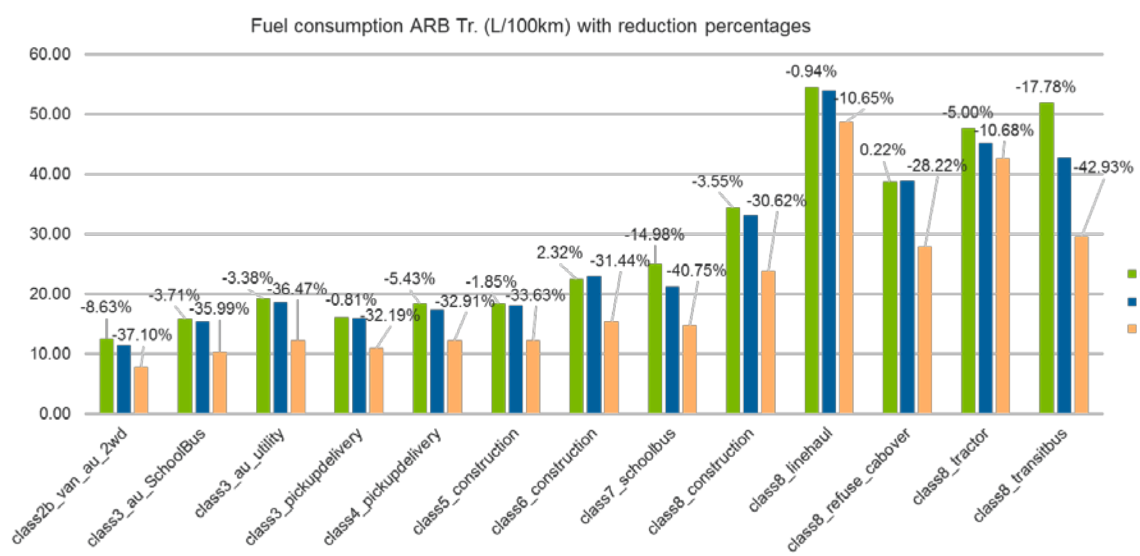

Figure III.5.3 - Fuel consumption of conventional and hybrid trucks on EPA65 cycle

Conclusions

A full report has been released describing the VTO technology impact for LDVs. For MD and HD vehicles, a comprehensive and extensive set of vehicle models have been developed to quantify the impact of advanced vehicle technologies. The technology roadmap developed for these vehicles is under review by DOE and industry partners. The new Autonomie models will be used to analyze how advanced technologies could impact the vehicle energy consumption and cost, to help DOE meet mission goals of economic growth, improved national security, reliability, and affordability.

Key Publications

E. Islam, A. Moawad, N. Kim and A. Rousseau, “An Extensive Study on Sizing, Energy Consumption, and Cost of Advanced Vehicle Technologies”. ANL/ESD-17/17, Argonne National Laboratory, Argonne, IL. 2017 (forthcoming)

E. Islam, A. Moawad, N. Kim and A. Rousseau, "Prediction of Electrified Vehicles' Energy Consumption and Cost Based On U.S. Department of Energy Targets". EVS30. Stuttgart, Germany. October 2017

R.Vijayagopal, A.Vallet, "Fuel consumption and performance benefits of electrified powertrains for medium and heavy duty vehicles", accepted at SAE World Congress 2018

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