U.S. DEPARTMENT OF
ENERGY

Office of
ENERGY EFFICIENCY &
RENEWABLE ENERGY

Analysis Program

2019 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 Analysis Program and the office as a whole, and enable important improvements in fuel economy and the efficiency of the transportation system as a whole.

The Analysis Program would also like to acknowledge Energetics for its 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 model
BEV	battery electric vehicle
CAV	connected and automated vehicle
CCS	carbon capture and storage
CF	characterization factor
CHP	combined heat and power
CO_2	carbon dioxide
CO_2e	carbon dioxide equivalent
DCFC	direct current fast charge
DOE	U.S. Department of Energy
DR	demand response
EEMS	Energy Efficient Mobility Systems Program
EERE	Energy Efficiency and Renewable Energy
EIA	U.S. 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
gCO_2e	grams CO_2 equivalent
GPRA	Government Performance and Results Act
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Transportation model
GWh	gigawatt hour
HDV	heavy-duty vehicle
HEV	hybrid electric vehicle
HWC	human water consumption
ISG	integrated starter generator
kWh	kilowatt hour
LDV	light-duty vehicle
MA3T	Market Acceptance of Advanced Automotive Technologies Model
mpg	miles per gallon
mph	miles per hour

MS	Microsoft Corporation
MSRP	manufacturer's suggested retail price
NEAT	Non-Light Duty Energy and GHG Emissions Accounting Tool
NG	natural gas
NHTSA	National Highway Traffic Safety Administration
NREL	National Renewable Energy Laboratory
ORNL	Oak Ridge National Laboratory
PDF	Portable Document Format
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
PV	solar photovoltaic
R&D	research and development
RE	renewable energy
SMART	Systems & Modeling for Accelerated Research in Transportation
SOC	State of Charge
TDP	Transportation Data Program
TOU	time-of-use
USDOT	United States Department of Transportation
EPA	U.S. Environmental Protection Agency
VMT	vehicle miles traveled
VTO	Vehicle Technologies Office

Executive Summary

During fiscal year 2019 (FY 2019), 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 2019. Each of the progress reports includes project objectives, approach, and highlights of the technical results that were accomplished during the fiscal year.

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Vehicle Technologies Office Overview

Vehicles move our national economy. Annually, vehicles transport 11 billion tons of freight—about $35 billion worth of goods each day[1]—and move people more than 3 trillion vehicle-miles.[2] Growing our economy requires transportation and transportation requires energy. The transportation sector accounts for approximately 30% of total U.S. energy needs[3] and 70% of U.S. petroleum consumption.[4] The average U.S. household spends over 15% of its total family expenditures on transportation, making it the most expensive spending category after housing.[5]

The Vehicle Technologies Office (VTO) has a comprehensive portfolio of early-stage research to enable industry to accelerate the development and widespread use of a variety of promising sustainable transportation technologies. The research pathways focus on fuel diversification, vehicle efficiency, energy storage, and mobility energy productivity that can improve the overall energy efficiency and efficacy of the transportation or mobility system. VTO leverages the unique capabilities and world-class expertise of the National Laboratory system to develop innovations in electrification, including advanced battery technologies; advanced combustion engines and fuels, including co-optimized systems; advanced materials for lighter-weight vehicle structures; 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) that leverage relevant expertise. These partnerships prevent duplication of effort, focus 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 that is too far from market realization to merit industry resources.

Annual Progress Report

As shown in the organization chart (below), VTO is organized by technology area: Batteries & Electrification R&D, Materials Technologies, Advanced Engine & Fuel R&D, Energy Efficient Mobility Systems, Technology Integration, and Analysis. Each year, VTO's technology areas prepare an Annual Progress Report (APR) that details progress and accomplishments during the fiscal year. VTO is pleased to submit this APR for Fiscal Year (FY) 2019. In this APR, each project active during FY 2019 describes work conducted in support of VTO's mission. Individual project descriptions in this APR detail funding, objectives, approach, results, and conclusions during FY 2019.

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[1] Bureau of Transportation Statistics, Department of Transportation, Transportation Statistics Annual Report 2018, Table 4-1. https://www.bts.gov/tsar.

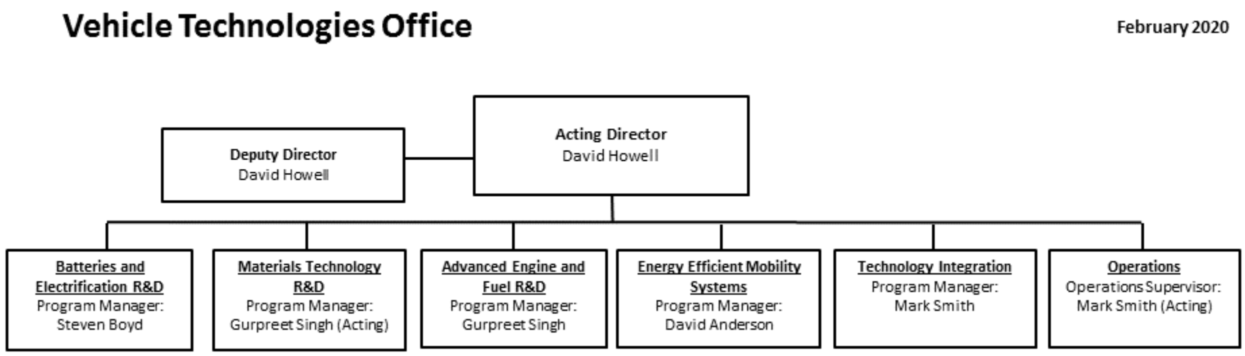
[2] Transportation Energy Data Book 37th Edition, Oak Ridge National Laboratory (ORNL), 2019. Table 3.8 Shares of Highway Vehicle-Miles Traveled by Vehicle Type, 1970-2017.

[3] Ibid. Table 2.1. U.S. Consumption of Total Energy by End-use Sector, 1950-2018.

[4] Ibid. Table 1.12. U.S. Transportation Petroleum Use as a Percent of U.S. Petroleum Production, 2018.

[5] Ibid. Table 10.1, Average Annual Expenditures of Households by Income, 2016.

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

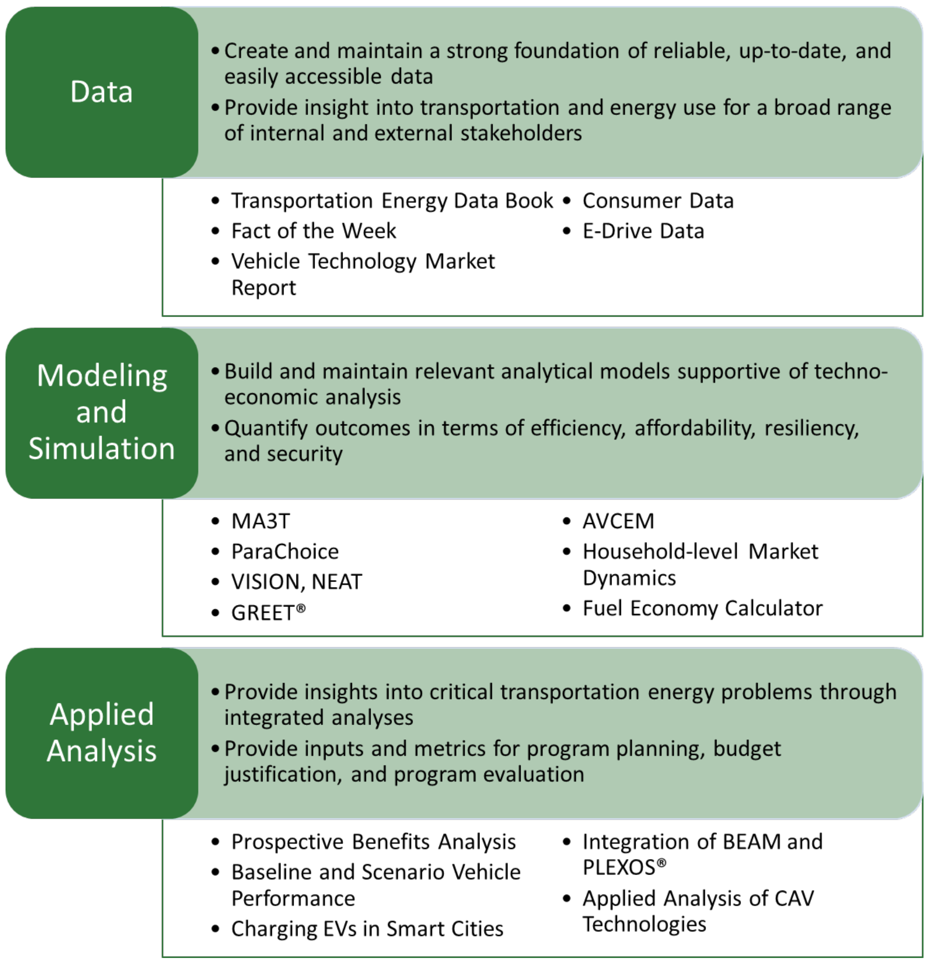
To achieve these goals, the Analysis Program supports activities with the following three broad objectives:

- 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 2019, 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 2019 Annual Progress Report and the EEMS FY 2019 Annual Progress Report.

I Analysis Program Project Portfolio

I.1 ISATT (Integrated Systems Technology Team) Analysis of Vehicle/Fuel Systems (Argonne National Laboratory)

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Start Date: October 1, 2018 End Date: September 30, 2019
Project Funding (FY19): $100,000 DOE Share: $100,000 Non-DOE Share: $0

Project Introduction

This project uses life cycle analysis (LCA) to estimate the life cycle energy use and air emissions of vehicle production, operation, and end of life for connected and automated vehicles (CAVs) across different powertrains and timescales for light-duty vehicles (LDVs). CAV technologies provide continuous road and vehicle monitoring and interactions, which may allow for safer vehicle operation, they may also induce reduced vehicle size, increased driving, and/or smoother driving. These will affect vehicle LCA performance.

Objectives

The goal of this research was to identify the potential life cycle issues that may be associated with CAV technology implementation and to quantify the total impact of such technologies, along with the additional vehicle changes they may induce, on vehicle energy use and emissions. The project considered internal combustion engine vehicles (ICEVs), hybrid electric vehicles (HEVs), battery electric vehicles (BEVs), and fuel cell electric vehicles (FCEVs). The LCA evaluation assumed a life cycle from 2020 to 2030.

Approach

For LCA, the project considered both the vehicle manufacturing and fuel cycles to account for the total cradle-to-grave energy use and emissions implications. The researchers accounted for manufacturing of the different vehicle powertrain technologies (the above-mentioned four different powertrains), along with manufacturing of CAV sensing and computing equipment. The project further evaluated the effect of CAV equipment operation on the energy consumption of different vehicle technologies. It was noted that CAV equipment may induce changes to both vehicle operation and the manner in which technology is adopted. The researchers considered scenarios with differing vehicle lifetime distances driven. All these factors were evaluated using the GREET® (Greenhouse gases and Regulated Emissions and Energy use in Transportation) model.

Results

CAV technology was evaluated for the ICEV, HEV, BEV, and FCEV for the years 2020, 2025, and 2030 with respect to the greenhouse gas (GHG) implications of each powertrain coupled with CAV technology, as well as consequent changes in vehicle components and energy demand. These results were also considered in the light of vehicle lightweighting (20% mass reduction), increased vehicle miles driven (i.e., longer operational life), smoother driving (yielding 15% energy reduction), and a possible battery replacement. The project also conducted a sensitivity analysis of results to each variable. If the CAV technology was not coupled with any benefits related to smoother driving or reduced vehicle mass, then its impact would be an increase in life cycle GHG emissions. However, according to other studies, lightweighting and/or smooth driving will likely be featured in these vehicles over time. At a 2,000 W power draw (sources indicate a large and uncertain range from 200 – 2,000 W for sensing and computing), there would be a reduction in GHG emissions for all powertrain technologies, assuming a degree of lightweighting and drive smoothing, as shown in Figure I.1.1.

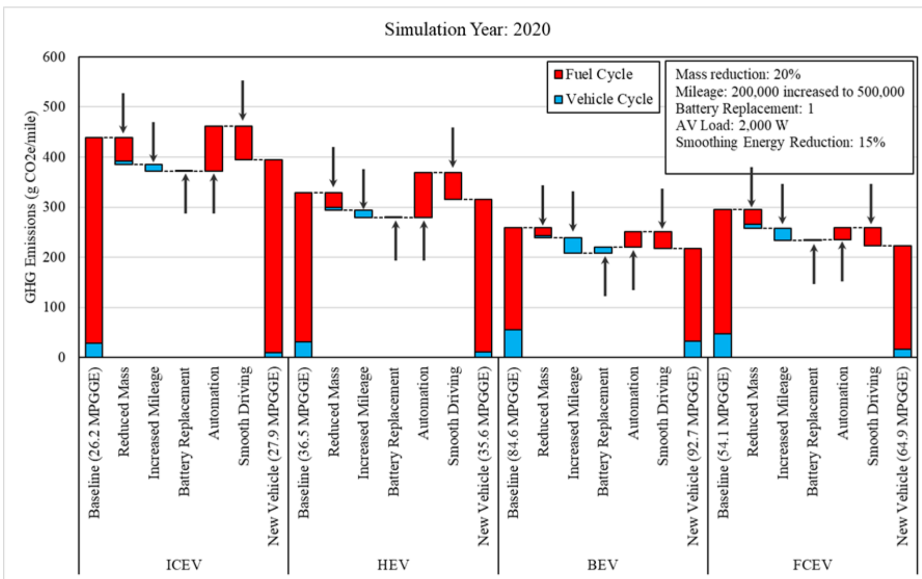

Figure I.1.1 GHG emissions for four different powertrain technologies (year 2020) using vehicle automation and assuming reduced mass, increased lifetime miles traveled, one battery replacement, a 2,000 W automation load, and smooth driving

Conclusions

Simulations suggest that the use of CAV technologies on LDVs will cause a slight increase in vehicle cycle emissions (i.e., the emissions associated with vehicle manufacturing), and the operations of automation equipment will increase the power demand of the vehicle, thereby reducing its fuel economy. The quantity of automation power demand is uncertain, ranging in the literature between 200 and 2,000 W per vehicle. The CAV technology may induce changes to the vehicle's design and operation, namely vehicle lightweighting and smoother driving, both of which may have a significant effect on energy use and hence GHG emission reductions.

Key Publications

Forthcoming

Acknowledgements

ISATT comprises the U.S. Department of Energy, energy and auto industries, and national laboratory researchers. The team acknowledges the support from experts from various organizations.

I.2 Life Cycle Analysis of Plug-in Electric Vehicles by Region Using Marginal Generation Mix (Argonne National Laboratory)

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Start Date: October 1, 2018 End Date: September 30, 2019
Project Funding (FY19): $100,000 DOE Share: $100,000 Non-DOE Share: $0

Project Introduction

Argonne National Laboratory coordinated work with Lawrence Berkeley National Laboratory (LBNL) to process its national grid modeling results. Researchers modeled different vehicle electrification penetration scenarios to develop marginal generation mixes for various electric utility regions. The marginal mix captures all electricity assets in a region that would be used in response to increased demand from vehicle electrification, while an average mix considers all regional assets on the electrical grid. These mixes were used to examine the life cycle emission factors of plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) in different regions. The analysis considered data from the National Household Travel Survey (NHTS) and vehicle stock projections using the Energy Information Administration's Annual Energy Outlook.

Objectives

The objective of this research was to characterize the average and marginal emissions of the electrical grid in various North American Electric Reliability Corporation (NERC) regions in the United States. The aim is to understand the effects of PHEV and BEV charging when considering average and marginal generation approaches. By considering these two different methods of assessing the impacts of battery charging on the electrical grid, the life cycle environmental emissions associated with PHEVs and BEVs can be estimated.

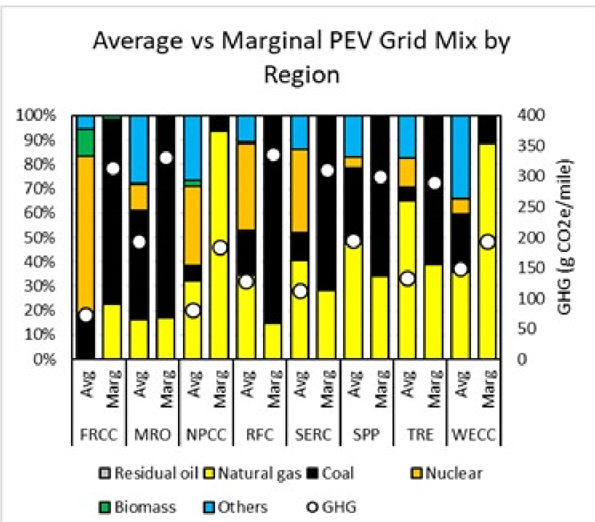
Approach

LBNL leveraged the Grid Operation Optimized Dispatch (GOOD) model to describe the electric grid's operation in responding to charging demand coming from plug-in electric vehicles (PEVs). The GOOD model is an economic dispatch model based on linear programming optimization. In general, the model dispatches generating units according to the lowest marginal cost, given cross-region bulk transmission constraints. This implies that, in most instances, renewable and nuclear energy with close to zero marginal cost are always dispatched first. By understanding the dispatch order for the electrical generating units within a region, the total energy production of each unit can be determined over time. In this case, dispatch was conducted over a limited time frame (one week), in the middle of each of the four seasons, to estimate the annual energy demand across the entire electric grid, both in absence of electrified vehicles and in response to their charging.

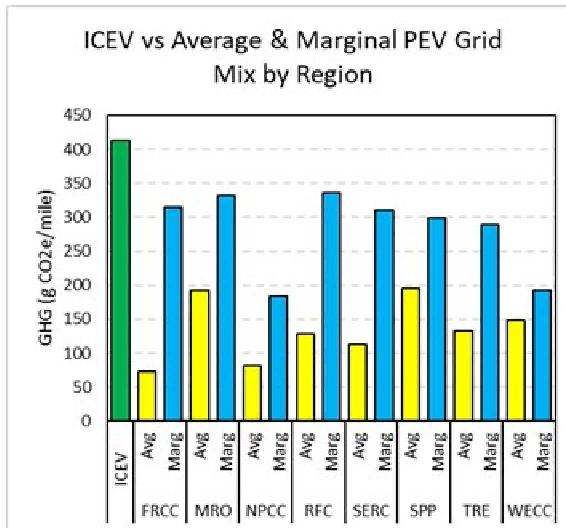
Vehicle charging parameters, including the time and rate at which PEVs are charged, were estimated for each vehicle type using simulations based on empirical charging data and considering both public and private charging options. The charging patterns were then used alongside the 2017 NHTS data for household travel to develop synthetic charging profiles. These charging profiles were overlaid onto the baseline electrical demand profiles and fed into the GOOD model to develop the marginal electricity profiles for PEVs in each region. These output profiles (fuel and technology mixes) were then incorporated into the GREET model to develop the characteristic emissions rates associated with each generation mix.

Results

Using the methods described above, the characteristic fuel and technology profiles were obtained for the different U.S. NERC regions. Those profiles were used within GREET to develop the consequent greenhouse gas emissions profiles associated with those average and marginal grid mixes, as shown in Figure I.2.1a. We observe from these results that the average fuel profile for each NERC region is comprised of a more diverse set of generating asset types than the marginal mix does. Furthermore, the greenhouse gas (GHG) emissions associated with the regional marginal electricity portfolio is greater than that associated with the corresponding average electricity mix. This indicates that the addition of electrified vehicles onto the grid will increase the GHG per-kWh associated with electricity generation if we follow the consequential analysis (i.e., use marginal generation mix). Even in that case, the electrically driven miles would still have a lower per-mile GHG emissions rate compared to the average gasoline internal combustion engine vehicle (ICEV) as is shown in Figure I.2.1b.



(a)



(b)

Figure I.2.1 a) The average and marginal life cycle GHG emissions associated with electric vehicle charging in 2018 in different U.S. utility regions, b) Comparison of the well-to-wheels GHG emissions per mile for an ICEV versus the average and marginal GHG emissions associated with electric vehicle charging in 2018 in different U.S. utility regions

Conclusions

The findings of this work indicate that there is a significant difference between using the average and the marginal grid GHG emissions on a regional basis, if the inclusion of PEVs is considered. Importantly, the project found that the marginal generation emissions for EV charging times and rates are greater in each region than the overall average generation emissions. Major reasons for this are both the time of charge (largely overnight) and the dispatchability of coal and natural gas assets compared to other assets. Furthermore, results show that differences from season to season are important for some regions, which indicates an area for further research, since there is evidence in the literature that energy consumption by PHEVs and BEVs is affected by high and low temperature conditions.

Acknowledgements

This work was conducted in collaboration with LBNL and the University of California at Davis. The Argonne National Laboratory team acknowledges the modeling and analysis support provided by Colin Sheppard and Alan Jenn from those two organizations, respectively.

I.3 Life Cycle Inventory Data Collection and Analysis for the Flow of Major Automotive Materials (Argonne National Laboratory)

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Start Date: October 1, 2018 End Date: September 30, 2019
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Project Introduction

This task investigated material flow analysis (MFA) and supply chain literature for iron, steel, and aluminum to evaluate and track the energy use associated with their production. This task formalized a methodology for conducting the MFA and developed data structures to facilitate execution. This analysis provides insight into the spatial impacts of automotive aluminum and steel, and allows analysis of other automotive materials.

Objectives

The materials database within the Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET®) model provides insight into the major automotive materials, along with many secondary and tertiary materials. These insights are limited by the spatial and temporal fidelity of material life cycle inventory data. Acknowledging the spatial heterogeneity of materials production, Argonne has previously conducted analysis of aluminum to elucidate the spatial variance. By examining the supply chain flows of major automotive materials, the life cycle impacts of producing automotive materials can be evaluated more accurately and with regional fidelity.

The objective of this task was to provide enhanced spatial resolution for several major automotive materials, including steel, iron, and aluminum, which together comprise nearly 80% of light-duty vehicle (LDV) mass. This task evaluates regional variation and source of these major automotive materials along the supply chain. This illuminates where automotive materials are sourced within the United States and allows a perspective of how much that material production contributes to the energy demands within the different regions.

Approach

MFA describes and quantifies stocks and flows of materials within a defined spatial and temporal system. It commonly uses commodity flow data into a system, and retirement rates from a system. MFA can be broadly classified into bottom-up or top-down approaches depending on the methods used, which are often influenced by data availability. Bottom-up MFA seeks to identify mass flows in the smallest common element of interest and sum those flows across all system elements—for example, identifying all steel within an LDV type in the U.S. automotive market for a given set of model years to determine the quantity of steel flowing and stored in the LDV market. A top-down MFA attempts to identify sectoral flows and trends, typically at the national level, to observe spatial and temporal flows of a material. For example, evaluating existing stocks of aluminum within each country using trade statistics to determine the net flow of aluminum for each country.

This project utilized a hybrid approach, leveraging data and techniques from both the bottom-up and top-down approaches, to construct and validate a database that considered the flows of aluminum and steel (and their precursors), both within the United States and abroad. Structural development of the material flows, using both real and synthetic (estimated) data, facilitated an analysis of the regional flows of aluminum and steel. These data identified the dominant regions within the United States for specific stages of automotive material production, thereby allowing more localized estimates of energy consumption and emissions for these sectors using life cycle analysis.

Results

The regional distribution of automotive aluminum mill mass flows is largely dominated by the NPCC (23%), SERC (20%), MRO (20%), and RFC (13%) North American Reliability Corporation (NERC) regions,[6] as well as an unresolved "Local" region (18%). Furthermore, all of the mill product mass flow in NPCC is due to aluminum sheet, while all of the mill product mass flow in "Local" is due to aluminum extrusions. Notably, the "Local" region accounts for ~58% of extrusions mass flow. However, extrusions represent only ~31% of the total amount of automotive wrought aluminum product by mass.

The regionality of automotive steel mill products is dominated by the RFC (63%) and SERC (20%) regions of NERC. The only other countries that supply over 1% of the total U.S. steel flow for automotive application are Canada (4.5%) and Turkey (1.1%). Separating automotive steel sheet products, the researchers found that the automotive steel mill products were still dominated by the RFC and SERC regions. The international countries that supplied over 1% of the total amount of each sheet product varied, but the combined total supply of these countries for each sheet product did not exceed 20%. Similar findings are observed for the hot-rolled bar and other steel product categories. While the RFC and SERC regions provide the majority of both hot-rolled bar and other steel supply, other NERC regions—WECC, TRE, MRO, and FRCC[7]—each exceeded 1% of the total supply. The large supply shares of these other NERC regions are due to hot-rolled bar and other steel being produced from electric arc furnace crude steel relative to sheet products.

Sensitivity analysis was conducted for all results, since many assumptions were needed to augment the publicly available data regarding the shipments and production statistics associated with both steel and aluminum. Those sensitivity analyses indicate that our broad identification of the key regions for both steel and aluminum production remains consistent.

Conclusions

Steel and aluminum are dominant LDV materials. The project identified important U.S. regions for automotive aluminum and steel production on a stage-by-stage basis. This allows for a regional life cycle analysis that evaluates more accurately the energy consumption and pollutant emissions associated with LDV production.

Key Publications

Hua, N., G. Lewis, and G. Keoleian (in preparation). "Regional-level analysis of the material flows and energy demands of aluminum in the American automotive industry."

Acknowledgements

This research was carried out in coordination with the University of Michigan's Center for Sustainable Systems. Argonne National Laboratory acknowledges the Center's participation, specifically the guidance of

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[6] Northeast Power Coordinating Council (NPCC), Southeastern Electric Reliability Council (SERC), Midwest Reliability Organization (MRO), and ReliabilityFirst Corporation (RFC) are NERC regions.

[7] Western Electricity Coordinating Council (WECC), Texas Reliability Entity (TRE), Midwest Reliability Organization (MRO), and Florida Reliability Coordinating Council (FRCC).

Prof. Gregory Keoleian, Dr. Geoff Lewis, and student researchers Nate Hua and Jon Newman. We thank industry professionals, including Jody Hall (AISI), Ron Krupizer (AISI [retired]), Yuki Kuwauchi (Nippon Steel), Ken Martchek (Alcoa), Mark Thimons (AISI), Marshall Wang (AA) and Brandie Sebastian (AISI), for their insightful discussions on the automotive aluminum and steel markets, support, and collaboration.

I.4 Estimates of Light-Duty Vehicle Cost Markup Factors (Argonne National Laboratory)

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Start Date: October 1, 2018 End Date: September 30, 2019
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Project Introduction

Knowledge of historical automotive original equipment manufacturer (OEM) manufacturing costs and intended sale prices of vehicles is important in understanding the costs and prices of current and emerging vehicle technologies, as well as the types of technology choices that OEMs may make in technology planning and deployment. Current practice within the U.S. Department of Energy (DOE), and elsewhere, is to translate estimated OEM manufacturing costs into sale prices using a markup factor. The most commonly used markup factor is 1.5. This study examined the state of the light-duty vehicle (LDV) cost markup factor literature. The aim was to understand the foundation of available markup factor formulations and describe how variations in assumptions may affect those factors. The study examined and evaluated literature to observe trends, such as markup factor variance and efforts to devise variable (non-linear) markup factors. Estimates of markup factors informed by this literature and analysis were investigated, along with some historical context.

Objectives

The task objective was to examine the LDV cost markup factor literature. The project examined publications, including DOE and national laboratory reports, and journal articles. Data from the literature were examined and evaluated for methodology and trends. Using the literature, mathematical formulations of markup factors were examined considering variations in vehicle markup factors due to variations in cost.

Approach

The manufacturer's suggested retail price (MSRP) is one way to identify price; however MSRP contains strategies that are proprietary to each OEM. Further, consumers may receive a variety of dealer incentives, discounts, rebates, and other tools that modify the MSRP. It is more common for researchers to examine the vehicle's retail price equivalent (RPE). The RPE is the vehicle sales price needed for the producer to earn a competitive rate of return on its manufacturing investment (EPA and NHTSA 2018). This study examined the literature to identify and synthesize the approaches taken by others to formulate these RPE values. Using this body of work, the project identifies the historical basis for the present-day use of the 1.5 RPE markup factor, and evaluates how components of cost might alter this final RPE value.

Results

This study examined the state of the cost markup literature for LDV. It found that there is consensus for a markup factor of 2.0 for vehicle parts produced by OEMs and a factor of 1.5 for parts that are outsourced. There is a wide acceptance that these values are not indicative of any specific part or OEM. Rather, they highlight that over time, the market (on average, across the OEMs' entire fleet) allows the OEMs to set their prices such that their return is consistent with the markup factors presented. Some vehicles will have higher markup factors and thus subsidize vehicles with lower markup factors. Further, from the mathematical formulations from Vyas, et al. (Figure I.4.1, and Rogozhin, et al., the project team observed that changes to manufacturing cost are the most influential in affecting markup factors, and that they are inversely proportional. Most other factors are directly proportional, although linearity should be taken not as a broad assumption but as a simplifying factor of the examined literature (Vyas, et al. 2000; Rogozhin, et al. 2009). U.S. Environmental Protection Agency and National Highway Traffic Safety Administration highlight that new technologies will initially have lower RPE values compared to mature technologies because of learning, advancements, and economies of scale (EPA and NHTSA 2018). So, while the project researchers did not find a specific variable markup factor approach that is widely accepted, they did examine the origins of the commonly identified 1.5 multiplier and the various factors that influenced it.

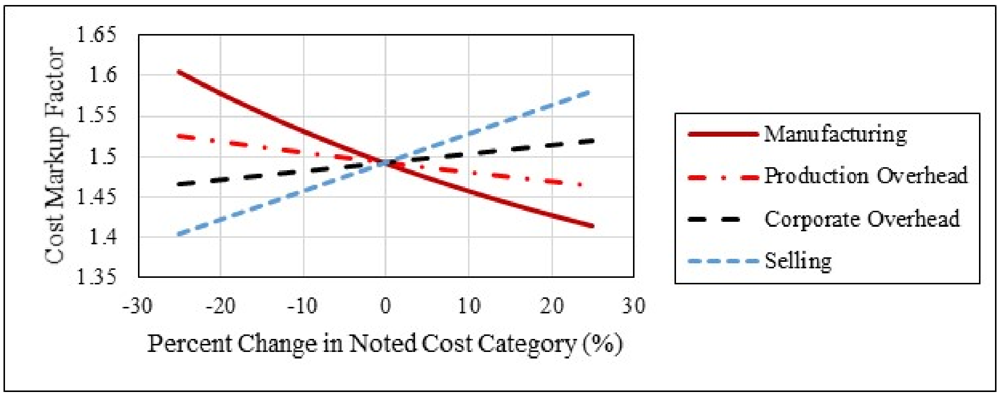

Figure I.4.1 Sensitivity analysis of outsourced part's markup factor from Vyas, Santini, and Cuenca (2000) due to variation in the listed components of cost

Conclusions

This literature review found consensus for cost markups of 1.5 and 2.0 for vehicle components that were outsourced or made in-house, respectively. Literature further suggests that new technologies initially have lower markup values compared to mature technologies because of advancements, learning, and economies of scale of production over time.

Key Publications

1. Kelly, J.C. (pre-submission). "Light-Duty Vehicle Cost Markup Analysis: Literature Review and Evaluation."

References

1. EPA and NHTSA (2018). "The Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for Model Years 2021–2026 Passenger Cars and Light Trucks." Proposed Rule NHTSA–2018–0067; EPA–HQ–OAR–2018–0283; FRL–9981–74–OAR.

2. Rogozhin, A., M. Gallaher and W. McManus (2009). "Automobile Industry Retail Price Equivalent and Indirect Cost Multipliers."

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Acknowledgements

The Argonne National Laboratory project acknowledges Rachael Nealer (DOE) for her direction on this project since its outset and continued support during its execution.

I.5 VISION/NEAT Annual Update (Argonne National Laboratory)

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Start Date: October 1, 2018 End Date: September 30, 2019
Project Funding (FY18): $150,000 DOE Share: $150,000 Non-DOE Share: $0

Project Introduction

Developed with U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) support over the past 15+ years, the VISION model and Non-light-duty energy and GHG Emissions Accounting Tool (NEAT) (https://www.anl.gov/es/vision-model, https://www.anl.gov/es/neat-nonlight-duty-energy-and-ghg-emissions-accounting-tool) address the need to assess fleet-wide energy use and emissions due to market adoption and technology advancement of various vehicle/fuel technologies. These tools track historical patterns and a long-term forecast of vehicle travel, fuel use, and emissions by mode and vehicle size/type. The tools allow users to conduct scenario analysis to compare with projections made by Information Administration's (EIA's) Annual Energy Outlook (AEO) Reference Case, and the U.S. Department of Transportation's (DOT) Freight Analysis Framework (FAF),

Objectives

The purpose of the project was to update VISION/NEAT to align the base case with annual AEO and FAF projections and release the models to users. VISION and NEAT were also to be revised to reflect energy and emission coefficients from the latest Greenhouse gases and Regulated Emissions and Energy use in Transportation (GREET®) model. Moreover, Argonne began developing an on-line version of the VISON model to facilitate wider access to, and easier use of, the model.

Approach

Estimates of fleet-wide energy use and emission effects must account for vehicle survival, technology trends, and macroeconomic factors such as gross domestic product and energy prices. VISION and NEAT were developed to serve this goal. Argonne used EIA AEO and DOT FAF forecasts, along with GREET energy and emission factors, to update the base cases of the two models with historical and projected data related to key inputs including market adoption, vehicle usage and efficiency, and mode shares. In 2019, VISION and NEAT were updated to align the base case with EIA AEO 2019 Reference Case and FAF4.0 projections. The tools were also revised to reflect energy use and emission coefficients from the GREET 2018 model release. The total energy consumption by fuel type and vehicle technology are calibrated to match with AEO projections. Users can change the inputs in these two models and compare their scenario results with the base cases. Major inputs of VISION include but not limited to light-duty vehicle (LDV) and heavy vehicle market shares, vehicle efficiency (MPGGE), vehicle miles traveled by powertrain technology, electricity generation mix, alternative fuel production share by feedstock. Major inputs of NEAT include ton-mile by commodity and by modes, modal energy intensity/efficiency (Btu/ton-mile) by commodity, fuel shares by mode (petroleum fuels, biofuels, electricity) and electricity generation mix.

For the online version of VISION, Argonne simplified the usage of the model compared to the Excel version. The first version covers only LDVs. The major user-defined inputs are market penetrations and fuel efficiencies of cars and light trucks, electric generation mix, annual VMT growth rate, and electric range of plug-in hybrid electric vehicles. VISION-online also has a graphic function to compare scenario results with "base case" results.

Results

With annual update efforts, Argonne updated and released the VISION 2019 version to users in September 2019. The "base case" in the most recent version of the model reflects projections of LDVs and HDVs in the EIA AEO 2019, as shown in Figure I.5.1. The EIA AEO 2019 projections end in the year 2050. In the update to VISION 2019, these projections were extended to the year 2100. For emissions calculations, the VISION model uses energy and emissions coefficients derived from Argonne's GREET model. The energy and emissions coefficients cover the full fuel cycle of various vehicle and fuel pathways. This release reflects emissions and upstream energy use from GREET 2018, as provided at http://greet.es.anl.gov/, and EIA AEO 2019 Reference Case data. The online version of VISION was developed and released at the end of September 2019. The current version is available at https://vision.es.anl.gov/Conclusions.

Conclusions

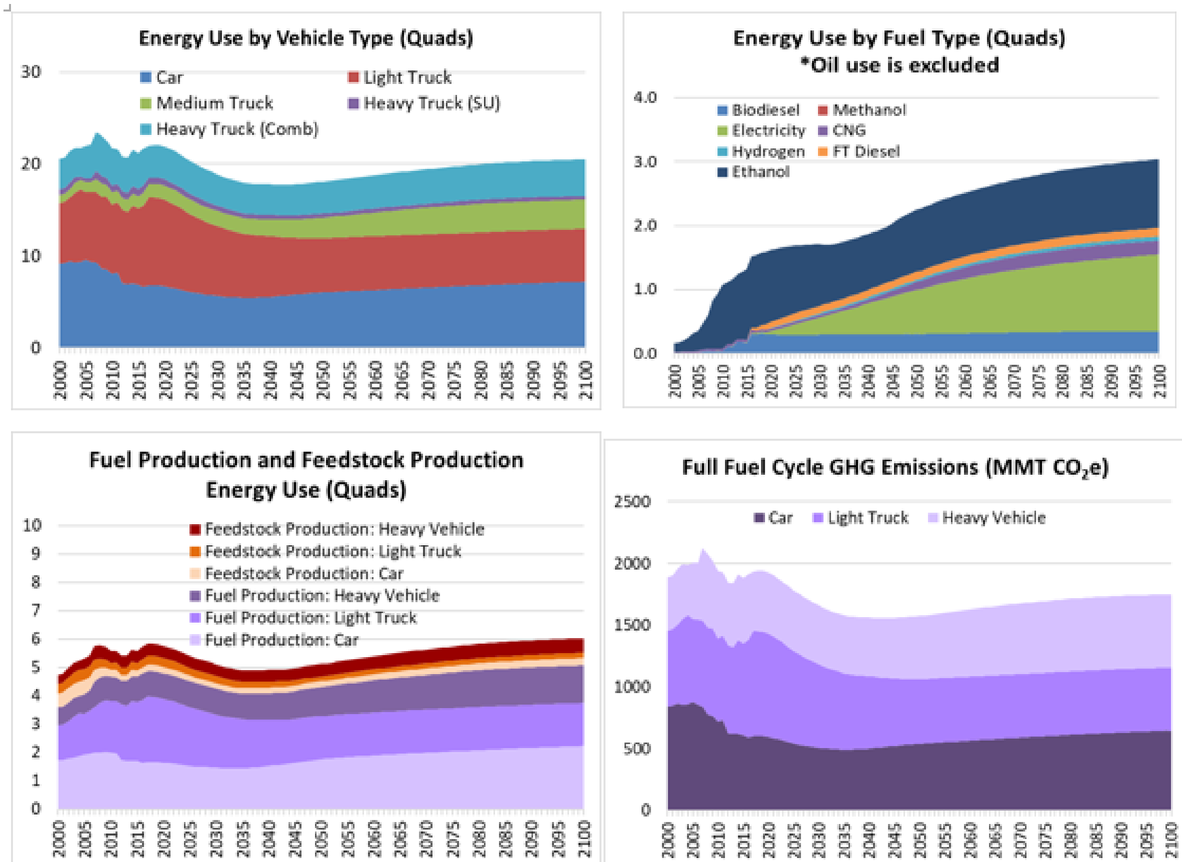

Figure I.5.1 VISION 2019 long-term base case results for LDVs and HDVs by fuel and vehicle type

Argonne's VISION/NEAT models were updated and calibrated to match the projections in the EIA AEO 2019 Reference Case and FAF4.0. Alternative powertrain technologies were added to medium- and heavy-duty trucks. Historical vehicles sales, stock, fuel economy, and other information were collected and documented in the models. VISION and NEAT models have been used by several DOE Office of Energy Efficiency and Renewable Energy programs and activities—such as the VTO Analysis Program, Prospective Benefits

Assessment, Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility, and H2@Scale—to evaluate the impacts of deploying advanced vehicle technologies.

I.6 Emerging Modeling and Simulations (Argonne National Laboratory)

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Start Date: July 2019 End Date: June 2020
Project Funding (FY19): $130,000 DOE Share: $130,000 Non-DOE Share: $0

Project Introduction

This project aims to understand the potential changes in energy consumption from conventional ownership of internal combustion engine (ICE) vehicles (today's most common case) to hybridized vehicles and non-traditional vehicle ownership scenarios. The project consists of two tasks, and their overarching purpose is to improve Vehicle Technologies Office (VTO) manager knowledge and awareness of these advances.

Objectives

Task 1 of this project examines the status of hybridized vehicles to understand how the light-duty vehicle market will evolve in the near future. Task 2 assesses the energy potential that alternative methods of vehicle ownership would allow through vehicle rightsizing.

Approach

Task 1: Market penetration of micro, mild, and full hybridization in ICE vehicles

As worldwide fuel economy standards become more stringent, automobile manufacturers are considering and implementing different degrees of vehicle hybridization and electrification. There are different levels of vehicle electrification, ranging from vehicles that use batteries only as engine starters to vehicles that use only electricity for propulsion. This task assesses the historical and projected forecasts and technology costs of micro-, mild-, and full-hybrid ICE vehicles. Oak Ridge National Laboratory will use the results in its Market Acceptance of Advanced Automotive Technologies (MA^{3}T) vehicle choice model to quantify the potential impact of ICE hybridization.

Task 2: Household vehicle rightsizing

A large fraction of driving in the United States is single-occupancy. According to the latest data from the National Household Travel Survey (NHTS), the average mileage-weighted vehicle occupancy is 1.67 total passengers per vehicle, which drops to 1.2 when considering commutes. Because commuters are often traveling alone, they would potentially be able to use smaller vehicles. This analysis compares the current real-world travel patterns for today's on-road vehicles with hypothetical right-sized vehicles, supplied through vehicle subscription services, carsharing, or ridehailing. These services allow consumers to use smaller vehicles for daily commuting while having the option for a larger vehicle as needs arise (e.g., family travel, hauling/towing, and recreational excursions).

Results

Task 1: Market penetration of micro, mild, and full hybridization in ICE vehicles

This task examined sales share forecasts from ten different organizations, considering both global markets and the domestic U.S. market. These studies project a wide range of results, with hybridized vehicles reaching between 7% and 34% of the U.S. market by 2025. Many of these analyses have been done over multiple years, with updated assumptions on vehicle technologies, regulatory requirements, and economic parameters. In general, these studies have tended to increase their projections for hybridized vehicles over time. Additionally, the project processed data from the Autonomie vehicle simulation model's forecasting of future vehicle cost and fuel economy; these data were used in the MA^{3}T vehicle choice model to find the potential market share of micro-, mild-, and full-hybrid vehicles. The MA^{3}T model shows that these hybridized vehicles can attain a high market share very quickly, and they would be more likely to take market share from conventional ICE vehicles than from plug-in electric vehicles.

Task 2: Household vehicle rightsizing

Using trip-level data from the NHTS, the project explored the number of vehicle trips that can be taken using smaller or more efficient vehicles. As shown in Figure I.6.1, most vehicle trips are taken by a single passenger. Of these trips, approximately half are taken in cars, and approximately half are taken in larger vehicles, such as SUVs, pickup trucks, and vans. Of these daily solo occupancy trips, one-third are trips to or from work. The solo trips in larger vehicles, shown in orange, are key opportunities for vehicle rightsizing.

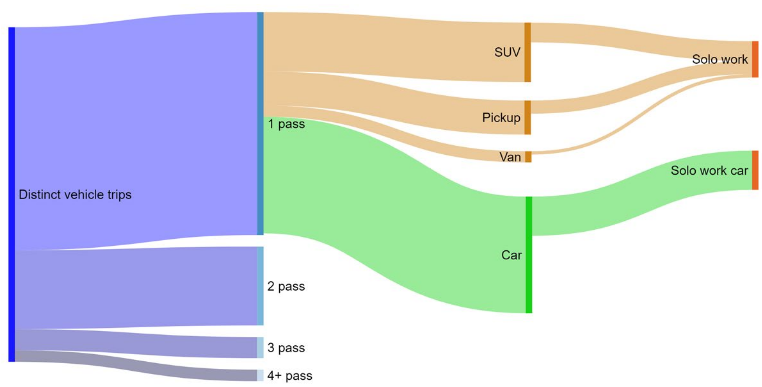

Figure I.6.1 Flow chart showing fraction of total trips that are solo work trips in vehicles that can be downsized. Data source: NHTS

With a vehicle subscription, a traveler can use a smaller car most of the time and then temporarily exchange this vehicle for a larger vehicle when necessary. The project found that 20% of daily trips use "over-sized" vehicles that never hold more than one passenger during the day, and are therefore potential candidates for vehicle subscription services. (Note it is possible that these vehicles may be hauling cargo necessitating a larger form factor for daily travel, and it is likely that many of these vehicles are used in trips with multiple passengers on days not surveyed in the NHTS.) This travel represents approximately 370 billion miles and 19 billion gallons of gasoline, annually. Replacing all of these trucks and SUVs with cars (equivalent to the average on-road car) would save over 5 billion gallons of gasoline per year. Replacement with a new high-efficiency hybrid electric vehicle would save nearly 11 billion gallons of gasoline annually.

Instead of targeting an entire day's travel, rightsizing each individual trip is representative of carsharing or ride-hailing. If all solo trips in larger vehicles instead took place in new cars available on demand, the change could affect 800 billion miles of vehicle trips, saving 15 billion gallons of fuel per year (when using conventional vehicles) or up to 23 billion gallons of fuel per year (with hybrid vehicles). While this degree of downsizing and vehicle sharing is likely not economically optimal (or logistically feasible), this analysis shows the extent to which vehicle fuel economy can be improved by using more appropriately sized vehicles.

Conclusions

Hybridized vehicles can grow in market share in the near future, and they would be more likely to take market share from conventional ICE vehicles than from plug-in electric vehicles. Vehicle rightsizing can show significant improvements in vehicle fuel economy and large savings in annual gasoline fuel consumption.

I.7 Autonomie Analysis

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Start Date: October 1, 2018 End Date: September 30, 2019
Project Funding (FY 2019): $200,000 DOE Share: $200,000 Non-DOE Share: $0

Project Introduction

Autonomie (www.autonomie.net) is the primary tool used by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) to analyze the energy consumption, performance, and cost of advanced vehicle technologies. Developed in collaboration with General Motors, Autonomie is a MATLAB®-based software environment and framework for automotive control system design, simulation, and analysis.

A large number of technologies need to be considered, and many of them might not yet be commercially available. Therefore, simulation tools are essential to evaluating the impact of the VTO research and development (R&D) portfolio at the national level. All the targets, data, and controls developed by the VTO analysis program are added to Autonomie to estimate the benefits of VTO's R&D. Any data or models developed with Autonomie are freely available to support any U.S. government-funded project. In the past year alone, Autonomie was used to support several agencies (in addition to VTO), including the DOE Fuel Cell Technologies Office, the U.S. Department of Transportation National Highway Traffic Safety Administration (NHTSA), and agencies under the U.S. Department of Defense.

Objectives

In fiscal year 2019, Autonomie was used to estimate the impact of advanced technologies across vehicle classes, from light-duty to heavy-duty.

Objectives for light-duty vehicle classes were as follows:

1. Compare the impact of DOE technology targets to that of specific current and near-term technologies.
2. Quantify the VTO cost–benefit analysis of current and future vehicles using the specific DOE vehicle component targets.

Objectives for medium- and heavy-duty (MDHD) vehicle classes were as follows:

1. Quantify the fuel-saving potential of advanced powertrains, including hybrid, plug-in hybrid, and battery electric in MDHD vehicles.
2. Quantify the impact of technology improvements expected in the long term (i.e., up to 2050).
    a. How will truck energy consumption evolve?
    b. How will truck ownership cost change over the next few decades?

Approach

Light-duty

Different vehicle attribute assumptions (frontal area, drag coefficient, etc.) were redefined, along with vehicle component weights (body, chassis, interior, etc.). Those models/data were updated in Autonomie (Autonomie 2019) for different vehicle classes. The Argonne report on NHTSA rulemaking analysis details the development of these assumptions (Islam et al. 2018).

The updated VTO target assumptions for different vehicle components—engine, lightweighting, electric machine, battery, etc.—across lab years 2015, 2020, 2025, 2030, and 2045 were applied across five different vehicle classes: compact, midsize, small SUV, midsize SUV, and pickup. To evaluate the impact of this wide range of VTO advances, several vehicle powertrain combinations were modeled. The powertrains considered in this study were:

- Conventional (gasoline–spark ignition [SI]/diesel–compression ignition [CI])
- Mild-hybrid belt-integrated starter generator (BISG) (gasoline–SI/diesel–CI)
- Conventional turbo (gasoline)
- Mild-hybrid BISG turbo (gasoline)
- Hybrid electric vehicles (HEVs)
- Plug-in hybrid electric vehicles (PHEVs)
- Battery electric vehicles (BEVs) of different all-electric ranges (AERs)

Medium- and heavy-duty

Before the commencement of this particular effort, vehicle models representing regulatory vehicles for MDHD trucks had been developed and integrated into Autonomie. This project defined performance requirements (e.g., 0–30 miles per hour) for each vehicle type/application. A performance-based sizing process was applied to various powertrain architectures to determine appropriate component sizes for all truck powertrain variants. In December 2018, DOE reviewed the preliminary results for energy consumption and manufacturing cost estimates. After the review, some of the assumptions were updated based on DOE feedback, and final results were generated for class, vocation, and powertrain combinations, as shown in Figure I.7.1. This report will briefly discuss the new results, which have been shared with other laboratories and partners for market penetration analysis.

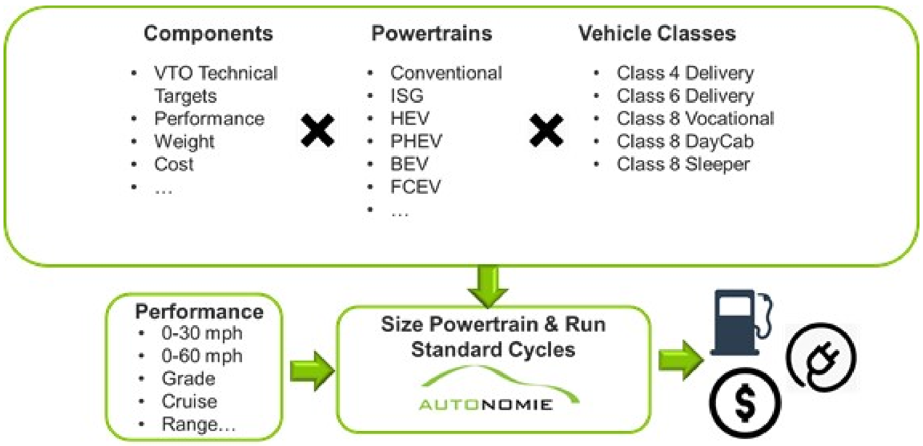

Figure I.7.1 Overview of the Autonomie analysis

Light-Duty Analysis: Vehicle Technology Impacts on Energy and Cost

The unadjusted fuel economy across different vehicle powertrains was analyzed for the different lab years simulated. Figure I.7.2 shows the results for the midsize car. The low technology progress scenario considers current improvements (i.e., without VTO breakthroughs), while the high case represents VTO targets.

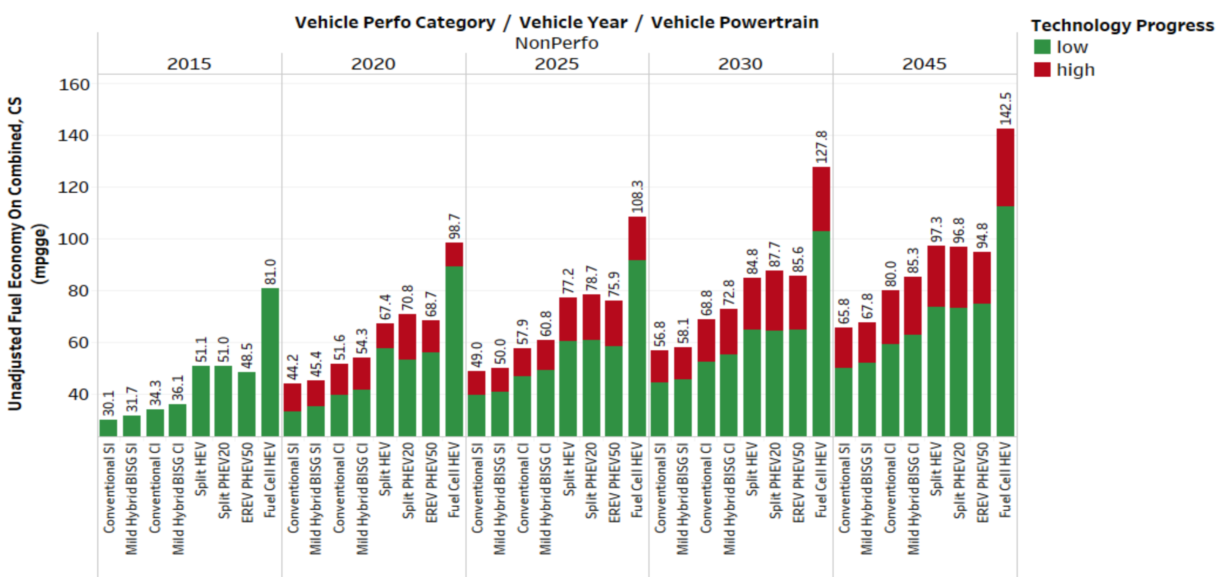

Figure I.7.2 Unadjusted fuel economy on combined charge-sustaining (CS) (mpgge) for midsize vehicle class

From the figure, it can be concluded that fuel economy improves significantly across all powertrains. For the midsize vehicle class, improvements by Lab Year 2045 compared to Lab Year 2015 for different vehicle powertrains due to achievement of VTO technology targets are as follows:

- Conventional gasoline: 118%
- Conventional diesel: 133%
- Conventional gasoline turbo: 117%
- Mild-hybrid gasoline: 114%
- Mild-hybrid gasoline turbo: 117%
- Split HEV: 90%
- Fuel cell HEV: 76%
- PHEV20: 90%

- Mid-hybrid diesel: 136%
- PHEV50: 95%

For conventional and mild-hybrid vehicles, engine technology improvements and lightweighting play a significant role in fuel efficiency benefits. For HEVs and PHEVs, improvements in the battery and electric machine also add to the benefits observed.

Figure I.7.3 shows the unadjusted electrical energy consumption for the midsize vehicle class for the different lab years simulated.

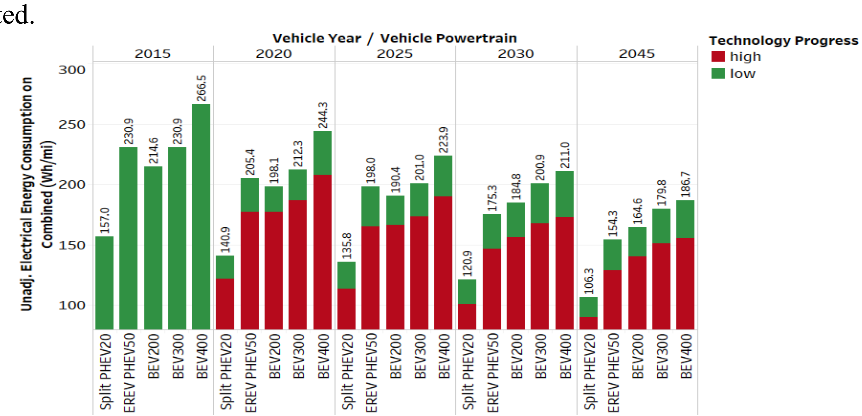

Figure I.7.3 Unadjusted electrical energy consumption on combined (Wh/mile) for midsize vehicle class

From the figure, it can be seen that, compared to the Lab Year 2015, the unadjusted electrical energy consumption for PHEV20 AER decreases by 43% by Lab Year 2045, by 44% for PHEV50 AER, by 35% for BEV200 AER and BEV300 AER, and by 42% by BEV400 AER. Most of the benefits for HEVs and PHEVs are driven by vehicle technology improvements (e.g., aerodynamics) and lightweighting. BEVs also benefit from lighter battery packs.

Figure I.7.4 details the vehicle manufacturing costs for the different vehicle powertrains in the midsize vehicle class for the lab years simulated.

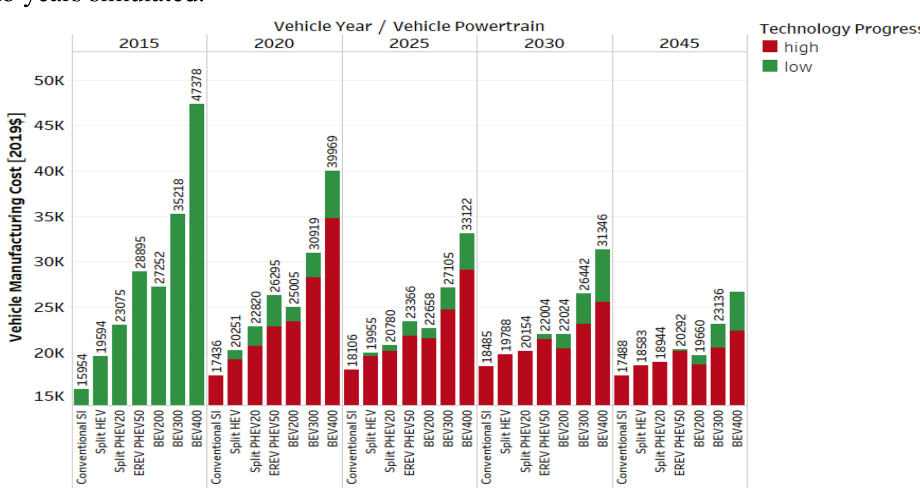

Figure I.7.4 Vehicle manufacturing cost of midsize vehicle class

The manufacturing cost for conventional vehicles (conventional/mild-hybrid) increases by 4%–10% by Lab Year 2045, compared to Lab Year 2015. The increase is driven mostly by a higher glider cost due to lightweighting. However, manufacturing costs for hybrid vehicles are predicted to decline, with decreases ranging from 7% to 53%. Vehicles with larger battery sizes (PHEVs and BEVs) tend to see the biggest improvement, owing to the advancements in VTO battery targets.

Figure I.7.5 shows the levelized cost of driving ($/mile) for different midsize vehicle powertrains across the lab years simulated.

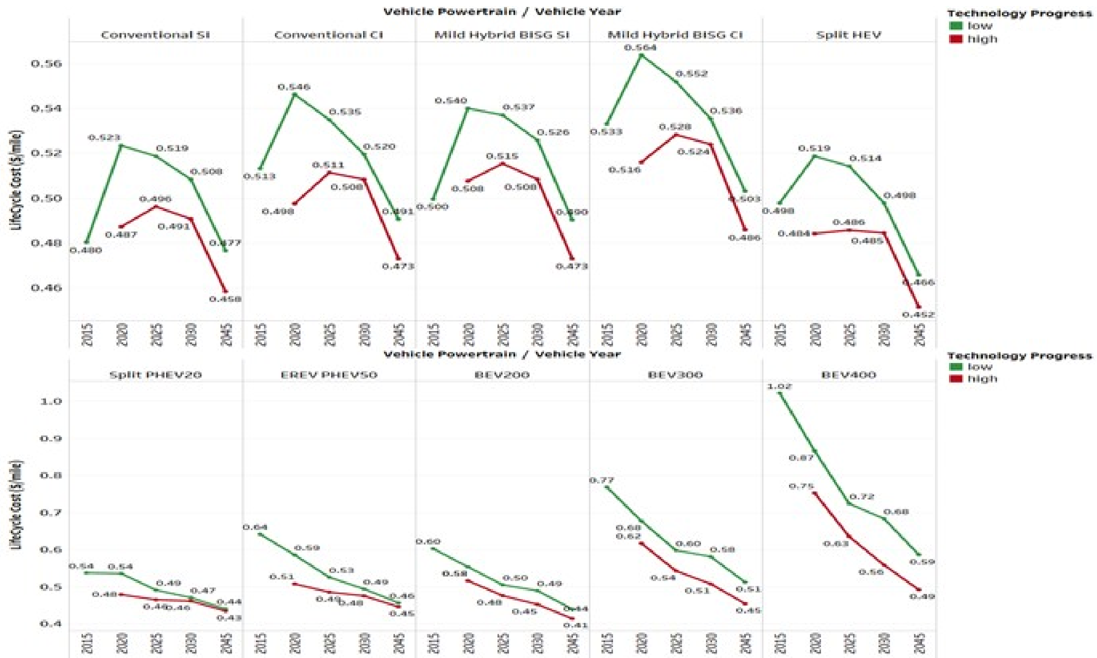

Figure I.7.5 Levelized cost of driving ($/mile) across for different vehicle powertrains

From the figure, the evolution of different vehicle powertrains can be observed in the context of levelized cost of driving ($/mile). For conventionals and power-split HEVs, glider cost increments affect the levelized cost of driving until Lab Year 2030. For the high-energy vehicle powertrains (PHEVs and BEVs), the impact of decreased electrified vehicle components costs (high-energy electric machines) offsets the glider cost impact and hence lowers the levelized cost of driving. The levelized cost of driving is higher for increasing AERs.

Medium- and Heavy-Duty Analysis: Vehicle Technology Benefits in Energy Consumption

As with light-duty vehicles, a large number of MDHD vehicle classes/applications were simulated in Autonomie to estimate the energy and cost of advanced technologies. To support further market penetration analysis, purchase price estimates and fuel consumption details were generated for each vehicle. Figure I.7.6 summarizes this information for various trucks considered in the market penetration analysis conducted by Energetics.

Figure I.7.6 shows a scenario in which the DOE targets are achieved over the next three decades. The prices for electrified powertrains gradually decrease, while all types of vehicles will reduce their energy consumption. Part of this improvement is attributable to innovations in lightweighting or aero drag reduction, which will benefit every vehicle. There are also battery-specific or fuel-cell-specific improvements that will benefit specific powertrains. A detailed report explaining the entire MDHD benefit analysis process is in final review by DOE and will soon be published by Argonne.

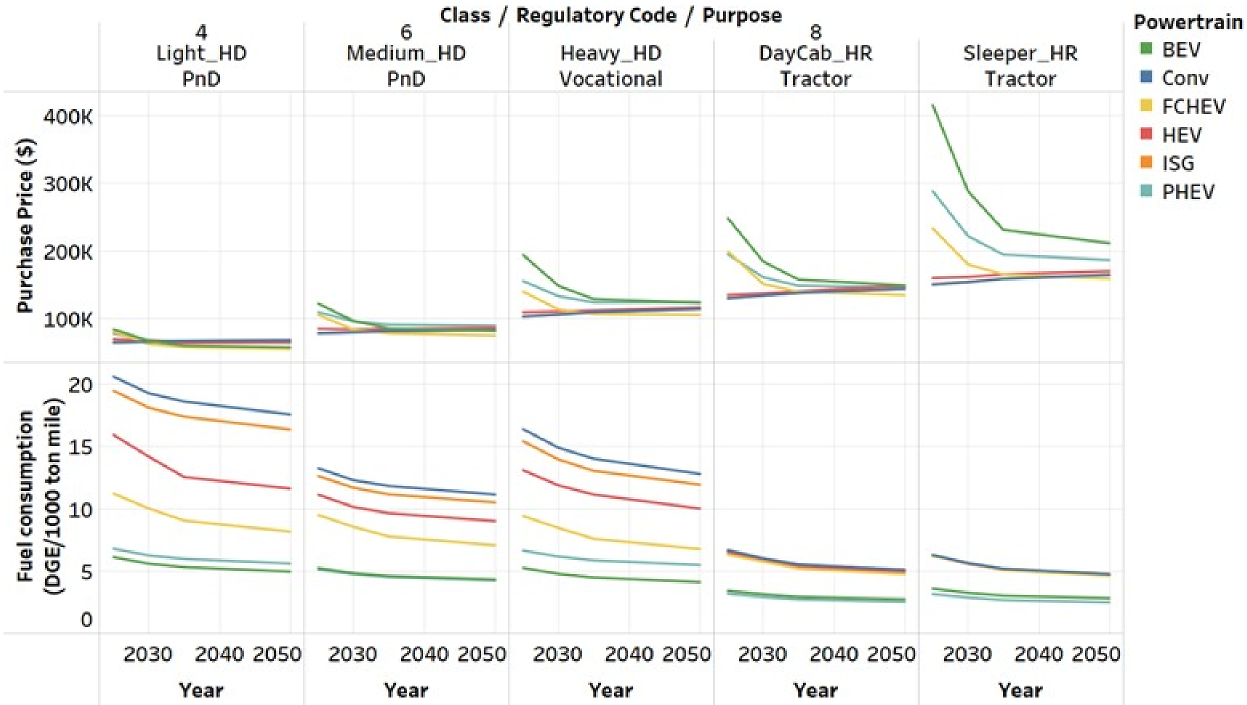

Figure I.7.6 Predicted fuel consumption and purchase price of various types of trucks

Conclusions

For the light-duty vehicles, energy consumption and manufacturing cost estimates were developed for different vehicle classes, vehicle powertrains, timeframes, and technology uncertainties. The results were provided to other national laboratories and agencies to support a wide range of analysis, including market penetration and life cycle analysis. A Tableau dashboard has been published on the Argonne server to allow DOE managers and researchers to compare the impact of near-term and long-term VTO benefits with current and near-term technologies. The analysis has also been used to quantify current and future material demands for energy storage systems (e.g., cobalt and nickel) and lightweighting.

A similar approach was used for MDHD vehicles. The reference trucks added to future Autonomie releases are already being used to support other DOE-funded activities. The powertrain-sizing algorithm has also been integrated into Autonomie to be used throughout the research community. A report on the MDHD analysis work is awaiting final approval from DOE.

Key Publications

1. Vijayagopal, R. and A. Rousseau (2019). "Fuel Consumption and Performance Benefits of Electrified Powertrains for Trucks." Presented at Electric Vehicle Symposium and Exhibition 2019 (EVS32).
2. Islam, E. and A. Rousseau (2020). "Future Cost Benefits Analysis for Electrified Vehicles from U.S. Department of Energy Target Advancements." Abstract submitted to Electric Vehicle Symposium and Exhibition 2020 (EVS33).
3. Islam, E. and A. Rousseau (2020). "Impacts of U.S. Department of Energy Lightweighting Target on Energy Consumption Benefits & Material Supply." Abstract submitted to SAE World Congress (WCX) 2020.
4. Islam, E. and A. Rousseau (2020). "Detailed Analysis of U.S. Department of Energy Engine Targets Compared To Existing Engine Technologies." Abstract submitted to SAE World Congress (WCX) 2020.

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I.8 Applied Analysis of Vehicle Technologies Benefits (Argonne National Laboratory)

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Start Date: October 1, 2019 End Date: December 31, 2019
Project Funding (FY19): $250,000 DOE Share: $250,000 Non-DOE Share: $0

Project Introduction}

The U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy's (EERE) Vehicle Technologies Office (VTO), in coordination with the Fuel Cell Technologies Office (FCTO) and Bioenergy Technology Office, seeks to better understand the potential energy, economic, and environmental outcomes of successfully reaching the goals of EERE vehicle research and development (R&D) programs. This analysis provides an assessment of the potential future benefits of advanced vehicle technologies being developed under VTO and FCTO R&D programs.

Objectives

The overall objective is to estimate the potential future benefits attributable to successfully achieving VTO and FCTO program goals. The benefits to be estimated include petroleum savings, cost reductions for consumers, and lower greenhouse gas (GHG) emissions out to the year 2050. The objectives for fiscal year (FY) 2019 were to update the inputs and the analysis methodology, to complete and document the analysis of program benefits of VTO and FCTO technologies in medium- and heavy-duty (MDHD) vehicles (started in FY 2018), to complete a new analysis of benefits in light-duty vehicles (LDVs), and to update the MDHD vehicle benefits analysis to make it consistent with inputs to the new LDV benefits analysis.

Approach

The approach is to develop and analyze two scenarios, comparing a possible future with completely successful development of VTO and FCTO technologies ("Program Success" scenario) to a future in which neither VTO nor FCTO makes any contribution to technology development after FY 2020 ("No Program," or baseline, scenario). Inputs for the Program Success scenario, including vehicle attributes, vehicle use, and refueling, were developed based on VTO and FCTO program goals, with additional details based on inputs from industry and Argonne National Laboratory (Argonne) experts.

For analysis of benefits in MDHD vehicles, the baseline scenario was derived from the Energy Information Administration's Annual Energy Outlook (AEO) 2018 Reference Case (AEO Ref Case 2018), but with VTO and FCTO technology R&D support removed. Inputs for the No Program scenario in LDVs were developed based on estimates of how advanced vehicle technologies would progress without further support from VTO and FCTO programs.

Argonne simulated vehicles using these inputs in Argonne's Autonomie toolkit (Argonne National Laboratory 2019) to provide vehicle fuel economy and manufacturing costs. MDHD vehicle purchase prices were estimated from manufacturing costs by applying markup factors. These markup factors were developed based on discussions with heavy vehicle manufacturers and on cost estimates reported by Schubert et al. (2015) in a report prepared for the National Highway Traffic Safety Administration's Phase 2 GHG and fuel economy standard regulatory analysis. For conventional diesel vehicles of each size class, current vehicle price information was obtained from online sources. These prices were used as baseline (No Program) vehicle prices through 2020 and were assumed to increase year-over-year at the same rate as the prices estimated from the Autonomie model. Incremental prices for the alternative powertrains (from Autonomie) were applied directly to baseline vehicle prices.

Fuel prices (except for hydrogen) were taken from the AEO Reference Case. Hydrogen price projections used in the Program Success case were consistent with FCTO program goals (Satyapal 2018); projections were more pessimistic for the No Program case. Both centrally refueled and non-centrally refueled fleets of MDHD vehicles were considered. Availability of hydrogen and electricity to non-centrally refueled fleets was based on extrapolations of electric charging and hydrogen fueling stations. Since future availability of these stations for MDHD vehicles was recognized as very uncertain, sensitivity to assumed availability was examined in a side case, described below.

Inputs for the two scenarios were used in market penetration models: the Energetics TRUCK model for MDHD vehicles and the Oak Ridge National Laboratory MA^3T model for LDVs.[8] New vehicle sales or sales shares were used in the Energetics HDStock model for MDHD vehicles and in the Argonne VISION model, to estimate the future on-road vehicle stock, energy use, and GHG emissions.

Updates to the MDHD benefits analysis are in progress. Since the LDV benefits analysis uses some inputs from the AEO 2019 Reference Case in the market penetration models and the VISION stock model, the MDHD vehicle benefits analysis is being updated to use the AEO 2019 Reference Case to maintain consistency. In addition, inputs on fuel system efficiency are being updated to new program targets developed by FCTO for heavy-duty fuel cell trucks.

Results

Advanced vehicle technologies supported by VTO and FCTO programs can greatly increase the fuel economy of MDHD vehicles. As a result of EERE-supported technologies, the sales-weighted average fuel economy of the entire on-road MDHD vehicle fleet, including all fuel types, is projected to be 10% higher in 2035, from 8.3 (No Program) to 9.1 (Program Success) miles per gallon diesel equivalent (mpgde), and 25% higher in 2050, from 8.8 to 11.0 mpgde.

The resulting petroleum savings in 2050 were estimated to be 0.71 million barrels per year, and reductions in GHG emissions in 2050 were estimated to be nearly 110 million metric tons of carbon dioxide equivalent (CO_2-eq) per year. Such petroleum reductions result in significant reductions in fuel expenditures for MDHD vehicles, totaling approximately $35 billion annually by 2035.

[8] Projections of LDV sales shares are also being developed using the Sandia National Laboratories ParaChoice model, but these projections were still being developed as of this report.

Figure I.8.1 shows the difference in projected changes on consumption of diesel fuel, electricity, and hydrogen between the No Program and Program Success scenarios, with negative values indicating reduction relative to the No Program scenario. Figure I.8.2 shows the reduction.

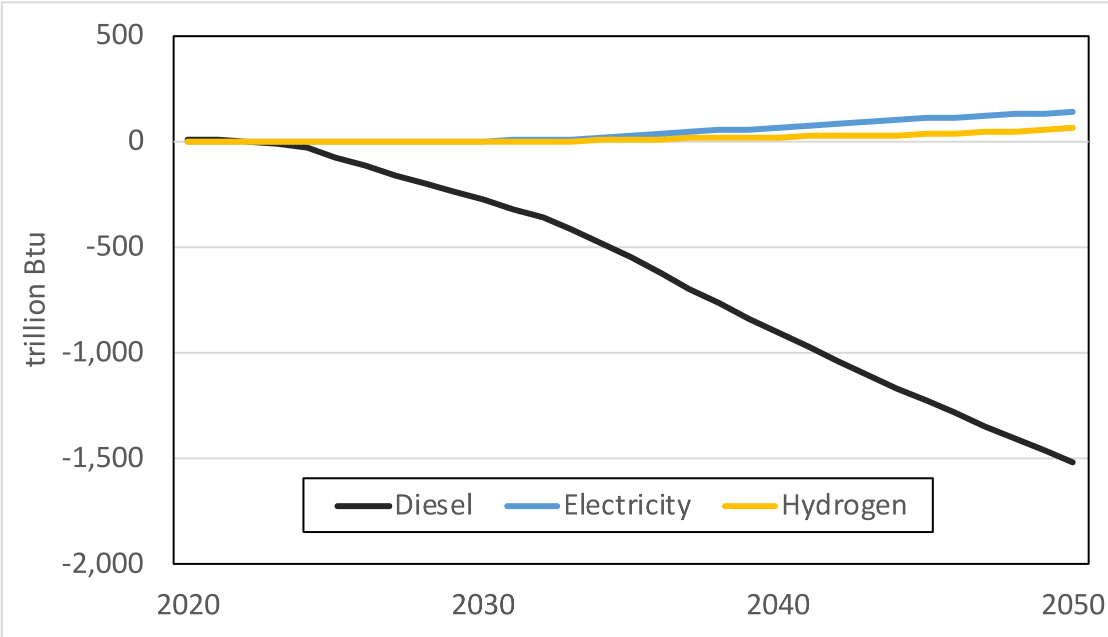

Figure I.8.1 Projected difference in energy use (all size classes) between the Program Success and No Program cases, for all size classes (negative values indicate reductions)

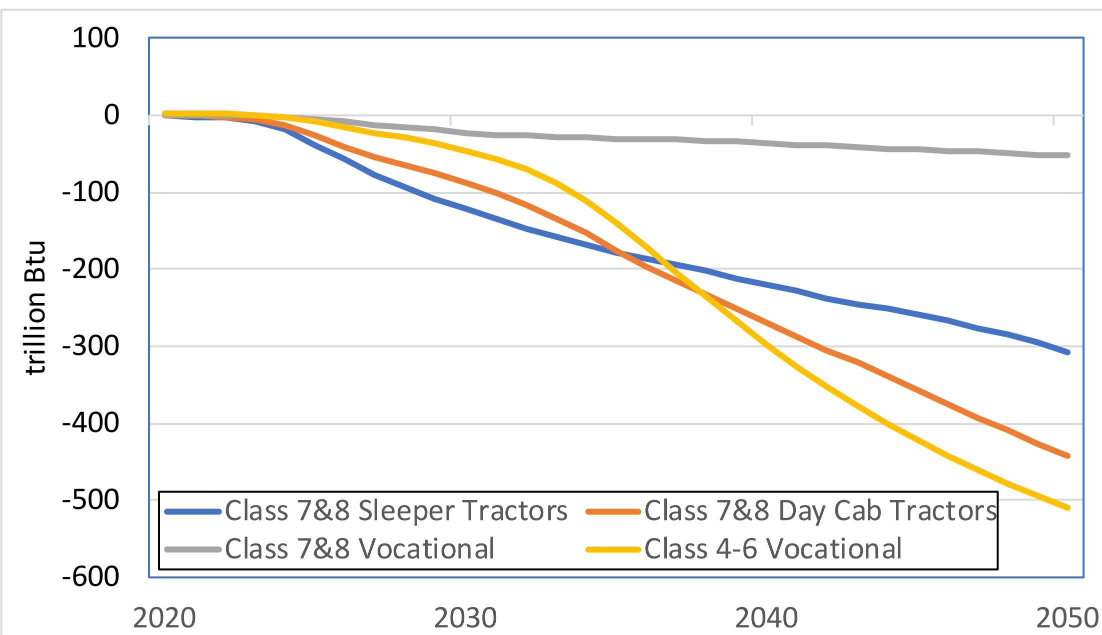

Figure I.8.2 Projected difference in energy use (all fuel types) between the Program Success and No Program cases, by size class bin (negative values indicate reductions)

Table I.8.1 lists other benefits estimated, including fuel economy improvement, reduction in annual fuel expenditures, and the cumulative reduction in GHG emissions. These results indicate that successful development and implementation of VTO technologies can significantly reduce petroleum use and GHG emissions from MDHD vehicles. The economic benefits of reduced fuel consumption and reduced prices of hydrogen are also significant. The many billions of dollars per year in reduced fuel costs is projected to greatly outweigh the projected increase in expenditures on new vehicles.

Table I.8.1 Projected Benefits of VTO and FCTO R&D in MDHD Vehicles

	2025	2030	2035	2040	2050
Oil savings rate (million bpd)[a]	0.03	0.13	0.26	0.43	0.71
New vehicle mpg improvement (percent)[b]	7	11	24	28	31
On-road stock mpg improvement (percent)[b]	1	5	10	16	25
Reduction in annual fuel expenditures	2.1	7.5	13.9	22.3	35.4
Increase in annual expenditures for new vehicle purchases (billion 2017$/year)[a]	2.5	2.6	2.8	3.6	4.0
GHG emissions reduction, cumulative (million tons CO_2-eq)[a]	12	102	280	572	1,476
GHG emissions reduction, annual (million tons CO_2-eq/year)[a]	-7	25	44	68	107

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 2020.

b Improvement relative to baseline (No Program) fleet in the same year.

Analysis of benefits in LDVs is still in progress, but preliminary results show the potential economic benefits of advanced vehicle technologies for LDV consumers. The levelized cost of driving (LCOD) was calculated for LDVs of different powertrains. The LCOD was calculated as the annualized cost of the vehicle purchase price and the annual cost of fuel divided by annual miles driven. Figure I.8.3 compares preliminary estimates of the LCOD of midsize cars with different powertrains in year 2030, assuming 13,500 miles/year and a 7% annual discount rate for 5 years. Successful achievement of VTO and FCTO program goals lowers both vehicle purchase prices and fuel costs.

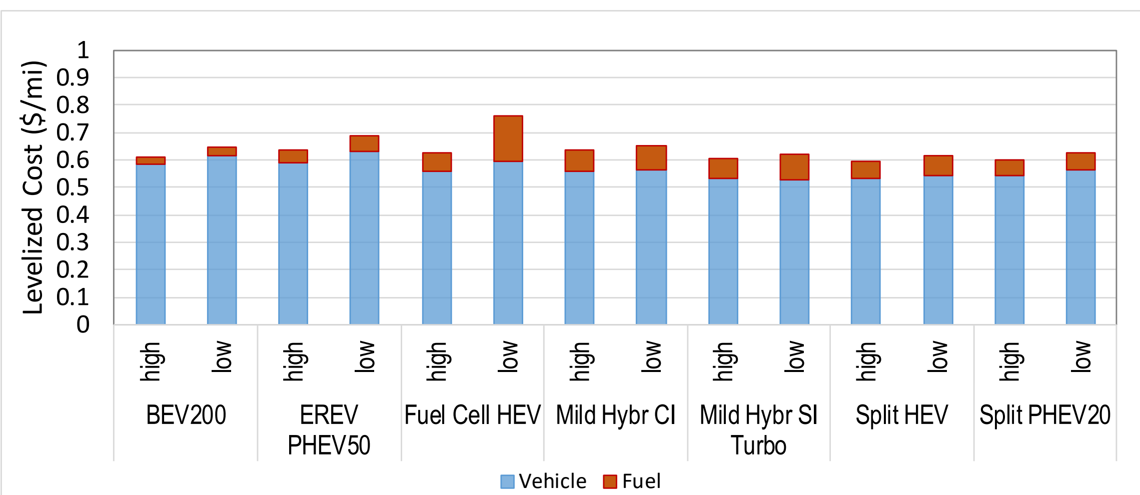

Figure I.8.3 Preliminary estimates of levelized cost of driving of midsize cars with different powertrains in year 2030, assuming 5 years, 13,500 miles/year, and a 7% annual discount rate (blue: vehicle cost per mile, red: fuel cost per mile)

Conclusions

This analysis provides an assessment of the potential future benefits of advanced vehicle technologies being developed under VTO and FCTO R&D programs. Two scenarios were compared: a Program Success scenario, representing a possible future with completely successful development of VTO and FCTO technologies, and a No Program (baseline) scenario, in which neither VTO nor FCTO makes any contribution after FY 2020 to development of these technologies. The difference in metrics such as projected petroleum consumption, GHG emissions, and expenditures on vehicles and fuel were estimated and found to be significant in MDHD vehicles. These results indicate that successful development and implementation of VTO technologies can significantly reduce petroleum use of, and GHG emissions from, MDHD vehicles. The associated reduced fuel consumption and lower hydrogen prices also carry significant economic benefits. Reduced fuel costs of many billions of dollars per year are projected to greatly outweigh the projected increase in expenditures on new MDHD vehicles. Analysis of these benefits in LDVs is in progress.

Key Publications

1. Stephens, T., R. Vijayagopal, M. Dwyer, A. Birky, and A. Rousseau (under review). Vehicle Technologies and Fuel Cell Technologies Office Research and Development Programs: Prospective Benefits Assessment for Medium- and Heavy-Duty Vehicles. Argonne National Laboratory Report.

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I.9 EV Sales Tracking (Argonne National Laboratory)

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Start Date: October 1, 2018 End Date: September 31, 2019
Project Funding (FY19): $50,000 DOE Share: $50,000 Non-DOE Share: $0

Introduction

Electric drive (e-drive) vehicle technologies include the hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), and battery electric vehicle (BEV). HEVs debuted in the U.S. market in December 1999, with 17 sales of the first-generation Honda Insight, while the first PHEV (Chevrolet Volt) and BEV (Nissan Leaf) more recently debuted in December 2010. E-drive vehicles are offered in several car and SUV models, as well as a few pickup and van models.

The U.S. Department of Energy's (DOE's) Vehicle Technologies Office (VTO) has supported analysis of light-duty market trends to assess potential benefits of VTO technologies and evaluate program activities. Historical sales and policy matrices (financial and non-financial incentives for vehicle purchase and operation) in the United States and other markets are not readily available, and there is limited understanding of regional advanced vehicle sales trends and consumer choice in the United States. Moreover, regional e-drive vehicle purchase trends need to be systematically examined to provide support and guidance for national impact analyses (e.g., potential energy and emission reduction) and infrastructure deployment. Understanding the aggregate impact of electric vehicles is important when exploring electricity use and petroleum consumption. Electric utilities are working to understand the changes in electricity generation, demand, and required infrastructure (EEI 2017; SEPA 2017). The growth of electric vehicles can offset petroleum consumption of conventional internal combustion engine (ICE) vehicles, affecting oil prices and extraction (OPEC 2018). Finally, refineries need to know the potential impact on demand for their refining mixes; gasoline and diesel are the two most common end products in the United States (DOE 2017).

Objectives

This project (1) collected e-drive vehicle monthly sales by make and model and tracked the technology and market trends and (2) quantified the energy and environmental impacts of e-drive vehicle adoption. Market trends included (but were not limited to) monthly and annual market shares, shares by automakers, correlation with economic factors (e.g., gross domestic product [GDP], gasoline prices, and unemployment rates). Energy and environmental impacts included (but were not limited to) miles traveled and gasoline consumption replaced by e-drive vehicles. The project provided monthly summaries of sales and market trends to DOE and subscribers. The project also published an annual report to document the market trend, technology evolution, and impacts of vehicle electrification.

Approach

The project collected monthly e-drive vehicle sales by make and model from various resources. Sales data were compiled from several sources at different points in time. Initially, the data were compiled from J.D. Power and Associates' sales reports and Electric Drive Transportation Association (EDTA) and HEV manufacturers' information. Later, the data were supplied by *Green Car Congress* and "Hybrid Market

Dashboard." At project end, the data were collected from *InsideEVs*, *WardsAuto*, and *Automotive News*. Civic hybrid sales numbers are as reported by Honda in 2003 and 2004. Data from 2005 and later represent sales as reported by EDTA, "Hybrid Market Dashboard," *InsideEVs*, and *Green Car Congress*. The Escape, Highlander, RX 400h, Camry, and GS 450h hybrid sales represent registration information from EDTA through 2006. The 2007 Escape and GS450h sales data are from *Green Car Congress*. Earlier Accord hybrid sales data are from EDTA and *Green Car Congress*. The 2007 Vue hybrid sales data (January to May only) are from EDTA, and later sales data are from "Hybrid Market Dashboard" and *Green Car Congress*. These numbers are by calendar year, not by model year as reported by the U.S. Environmental Protection Agency (EPA) in its "Light Duty Automotive Technology, Carbon Dioxide Emissions and Fuel Economy Trends Report." The HEV percentage shares reported by the EPA are for vehicles weighing <= 8,500 lbs., while shares reported here are for vehicles weighing <=10,000 lbs. Historical sales of e-drive vehicles, as well as technology and market trends, have been compiled by Argonne and provided in a Excel file to VTO each month. All other subscribers have also received monthly updates in which HEV sales are aggregated. Selected data are published on Argonne's website:

https://www.anl.gov/es/light-duty-electric-drive-vehicles-monthly-sales-updates.

A report written last year, "Impacts of Electrification of Light-Duty Vehicles in the United States, 2010–2017" (Gohlke and Zhou 2018) documents the details of the methodology used to estimate vehicle miles traveled, weighted efficiency, and the resulting gasoline replaced. Much of the methodology is similar, though estimations have been updated this year with improved data when possible. The data used in this assessment were compiled largely from publicly available data. Compiling data on vehicle sales and characteristics allows for a comprehensive assessment of the historical impacts of plug-in electric vehicles (PEVs) in the United States. The all-electric range, vehicle efficiency, size class, electric motor power, and manufacturer's suggested retail price (MSRP) of each model come from the FuelEconomy.gov database, managed by DOE and EPA (DOE and EPA 2019). Vehicle assembly and origin of parts come from American Automobile Labeling Act data from the National Highway Traffic Safety Administration (NHTSA) (NHTSA 2018); this information was supplemented by manufacturer press releases and news stories. Vehicle acceleration and battery capacity for each vehicle were established through a mix of data compiled by *InsideEVs* (Kane 2018), press releases, news stories, and information on manufacturer websites.

Results

Argonne tracked monthly U.S. e-drive vehicle sales by make and model and released monthly reports to over a hundred subscribers. Subscribers are from diverse agencies including automotive original equipment manufacturers, federal and state agencies, universities, and research institutes. Reports summarized monthly and annual sales trends and correlations with other economic factors such as GDP, gasoline prices, and unemployment rates. Argonne's e-drive sales data has supported DOE Office of Energy Efficiency and Renewable Energy (EERE) programs and activities such as eGallon, Workplace Charging, the Vehicle Market Report, and the EERE transportation Fact of the Week. Example charts in the monthly summary are shown in Figure I.9.1 and Figure I.9.2. Figure I.9.1 shows annual total BEV and PHEV sales. More than one million PEVs have been sold in the United States since 2011. Over 360,000 PEVs were sold in the United States in 2018, an 85% increase over 2017 mainly due to sales of Tesla Model 3. In 2018, nearly two-thirds of annual PEV sales were BEVs. Figure I.9.2 shows cumulative sales of all PEVs and top-selling models. "Other" in Figure I.9.2 includes more than 20 different models.

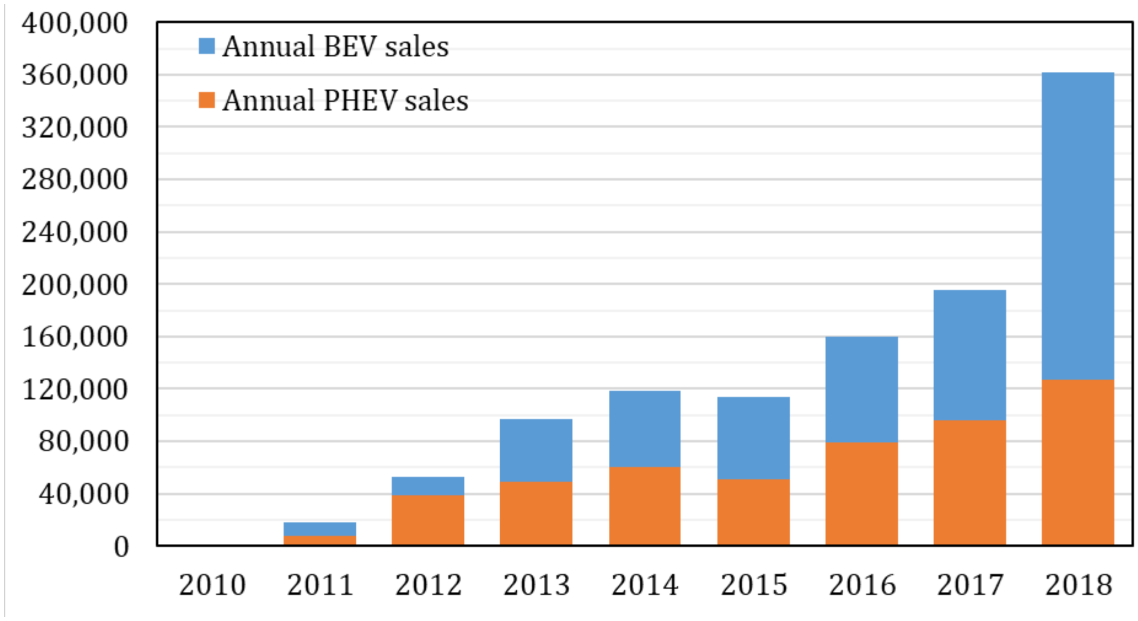

Figure I.9.1 PEV annual sales in the United States

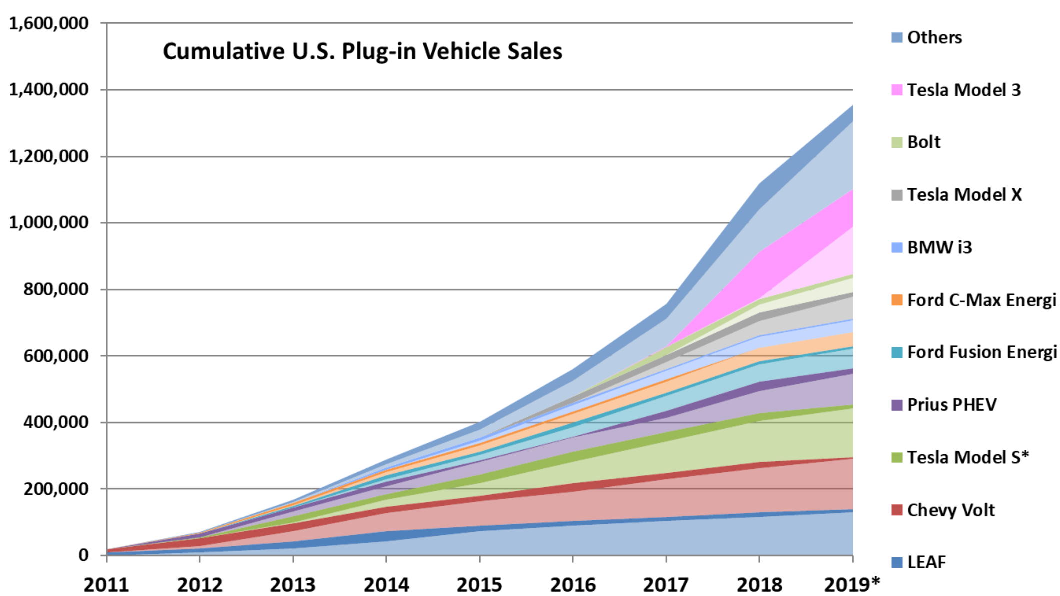

Figure I.9.2 Cumulative U.S. PEV sales (updated to September 2019)

Given the total number of monthly PEV sales, the all-electric range, and the effective utility factor for each vehicle, the total mileage driven in all-electric mode across the entire national light-duty vehicle (LDV) fleet can be estimated, as shown in Figure I.9.3. The utility factor for PHEVs used in this study comes from the Society of Automotive Engineers (SAE) J2841 standard (SAE, 2010), specifically the multi-day individual utility factor (MDIUF). This analysis suggests that electricity has powered more than 25 billion miles driven through 2018. In 2018, LDVs using electric power were estimated to have driven 8.6 billion miles on the road; BEVs account for approximately 62% of this mileage. This analysis indicates that in 2018, the average BEV drove 11,600 miles, while the average PHEV drove 7,300 eVMT.

PEV electricity use displaces gasoline that would otherwise be used by an ICE vehicle. Estimating this reduction in gasoline consumption requires assumptions about how each mile would have otherwise been traveled. For each PEV, the project selected a comparable ICE in the same size class and model year (rather than comparing with a fleet-wide average) to calculate the gasoline consumption offset by using electricity. For example, a compact PEV offsets the fuel consumption of a compact ICE vehicle. Given that early adopters of electric vehicles are often interested in fuel economy and environmental benefits, the comparable gasoline ICE vehicle was assumed to be more fuel-efficient than average, specifically, the 75th percentile of models available in that year and size class. The total annual gasoline displacement under these assumptions is shown in Figure I.9.4; other findings include:

- In 2018, 320 million gallons of gasoline were offset by PEVs, with 64% of this total offset by BEVs.
- In 2018, the average BEV offset 450 gallons of gasoline, and the average PHEV offset 260 gallons.
- Cumulatively, through 2018, PEVs have offset over 940 million gallons of gasoline, 585 million gallons by BEVs and 363 million gallons by PHEVs.

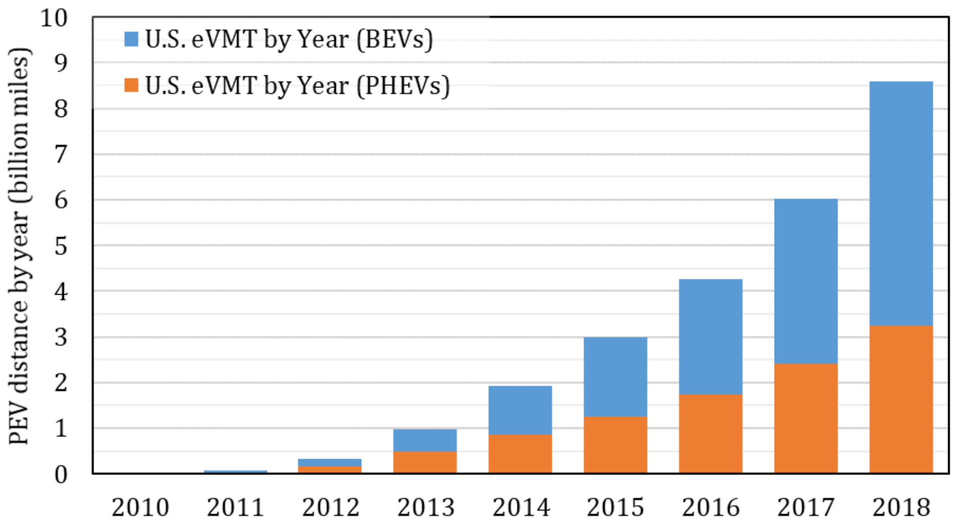

Figure I.9.3 U.S. eVMT by PEVs by year

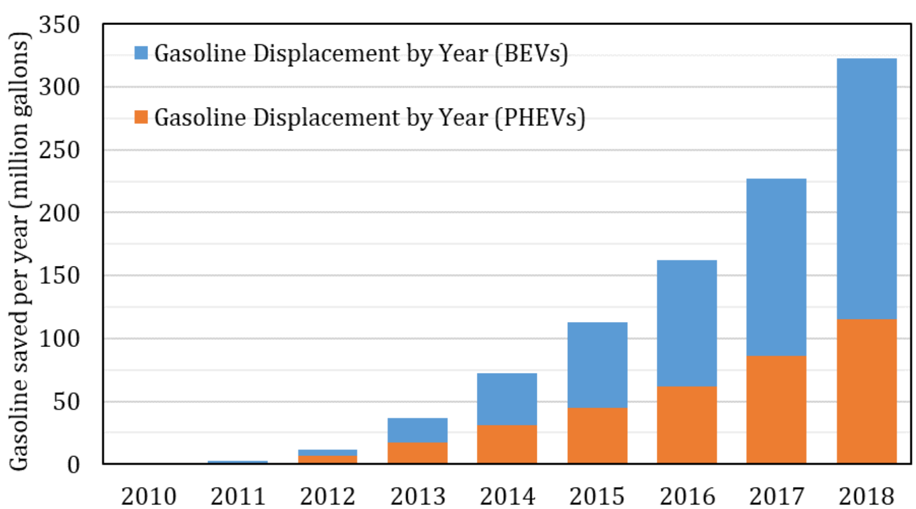

Figure I.9.4 Gasoline displacement from ICE vehicles by LDV PEVs by year

Conclusions

PEV sales and PEV market shares of all LDVs have been increasing in the United States since the first introduction in December 2010. More than one million PEVs have been sold in the United States since 2011, with over 360,000 sold in 2018, an 85% increase over 2017. Slightly over half of 2018 PEV sales were BEVs. PEVs account for about 2% of all LDV sales monthly in 2018.

Since the latest generation of light-duty PEVs became available in the United States, more than one million PEVs have been sold, and are estimated to have driven more than 25 billion collective miles on electricity. These 25 billion eVMT represent more than 8.4 terawatt-hours of electricity and a nationwide gasoline consumption reduction of 950 million gallons. PEVs account for increasing numbers of miles driven, offsetting gasoline consumption and CO_2 emissions from ICE vehicles.

Key Publications

1. Gohlke, David and Yan Zhou (2019). Impacts of Electrification of Light-Duty Vehicles in the United States, 2010–2019. Report ANL/ESD-19/2.

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Acknowledgements

Thanks to Dr. David Gohlke of Argonne National Laboratory for his contribution to this work. Dr. Gohlke is also the leading author of the above-listed key publication.

I.10 Plug-in Electric Vehicle Benefits (Lawrence Berkeley National Laboratory)

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Start Date: October 2017 End Date: September 2019
Project Funding (FY19): $250,000 DOE Share: $250,000 Non-DOE Share: $0

Project Introduction

Increasing levels of renewable energy are being added to the electric grid, at the same time that vehicle electrification is on the rise. The impacts of the integration between these technologies require new analytical methodologies that couple capabilities across the transportation and power sectors. This report assesses the benefits of light-duty vehicle electrification using the Grid-Integrated Electric Mobility model (GEM), a national model of electrified mobility and economic dispatch of power generation.

The transportation sector is transforming through the introduction of on-demand mobility and through vehicle automation (Greenblatt and Shaheen 2015). These advances, combined with electrification, could create new synergies that would provide high-quality, low-cost, and energy-efficient mobility at scale (Sperling n.d.; Fulton 2018).

However, adoption of plug-in electric vehicles has been relatively slow for several reasons, including technological uncertainty, slow charging, range anxiety, and higher capital costs compared to other types of vehicles (Green, Skerlos, and Winebrake 2014). While there is still a great deal of uncertainty around the impact that automated vehicles will have on the transportation system in the coming decades (Stephens et al. 2016; MacKenzie, Wadud, and Leiby 2014), many believe that they will soon be a part of the transportation system and could dramatically disrupt conventional modes of mobility.

Shared automated electric vehicles (SAEVs) could offer on-demand transportation in electric and self-driving cars, similar to the service provided by current transportation network companies but at a much lower cost (Chen, Kockelman, and Hanna 2016). Each SAEV need have only enough seats and battery range for the trip requested (fewer seats in a smaller car is a strategy known as “right-sizing”), and charging can be split over many short periods in between trips; therefore, the shared mobility paradigm could enable the use of smaller cars with shorter battery ranges, thus overcoming the barriers of slow charging speed and high capital cost (Bauer, Greenblatt, and Gerke 2018).

This project developed the GEM model to explore the dynamics of an integrated transportation–grid system in which mobility is served by either personal electric vehicles (EVs) or SAEVs, charging is responsive to costs on the grid, and power resources are dispatched in merit order to serve electricity demand.

Objectives

The purpose of this project was to develop new methodological capabilities that enable the estimation of national EV–grid impacts in terms of power sector operational costs, and energy demand for scenarios involving both personally owned EVs and fleets for automated, mobility-on-demand EVs.

Approach

The project developed an optimization model that solves for the cost-minimizing dispatch of personal EV and SAEV charging, the allocation of SAEVs to serve mobility, the construction of an SAEV fleet and supporting charging infrastructure, and the economic dispatch of generation resources on the bulk transmission grid. The power sector was included by coupling GEM to the Grid Operation Optimized Dispatch (GOOD) electricity model. This combined model treats the size of the SAEV fleet and the amount of charging infrastructure as continuous decision variables (relaxing the problem from mixed-integer to quadratic), allowing for heterogeneous vehicle ranges and charger levels. The model minimizes operational costs by choosing the timing of fleet recharge while requiring that mobility demand be served, that energy be conserved, and that generation assets on the grid be dispatched in merit order. SAEV fleet planning costs are simultaneously minimized by amortizing the cost of the fleet and charging infrastructure to a daily time period.

In addition to developing the optimization model, the project curated a set of empirically derived inputs and assumptions for the model application (Figure I.10.1). Several project assumptions were also developed through detailed, agent-based simulation modeling using the Routing and Infrastructure for Shared Electric Vehicles (RISE) model and from simulations completed by the National Renewable Energy Laboratory using EVI-Pro.

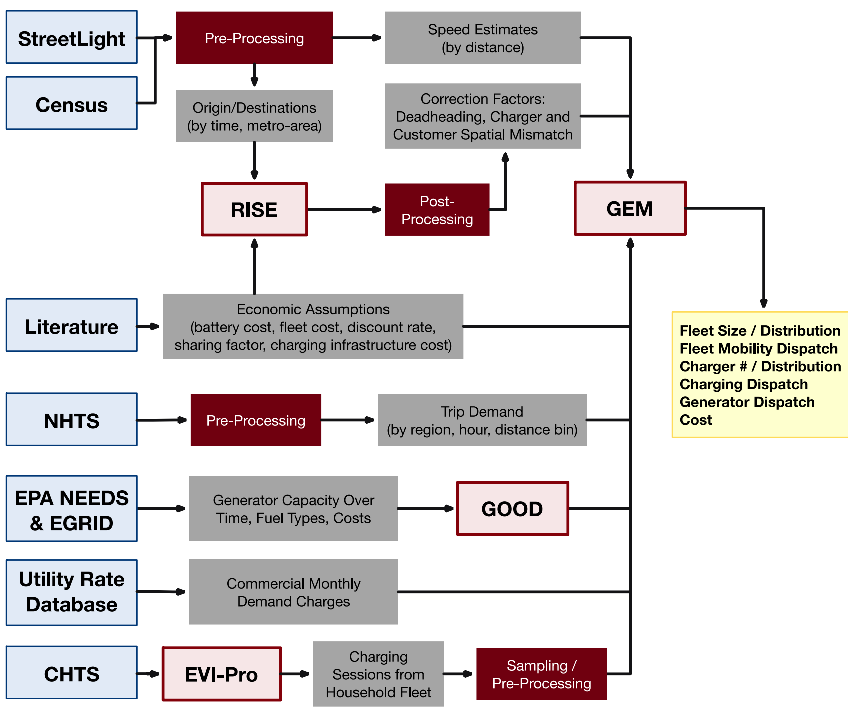

Figure I.10.1 Sources of data (blue), data processing (dark red), models (light red), intermediate data (grey), and model outputs (yellow) in the overall modeling and processing workflow

The project analysis considered several scenarios to provide sensitivity around the baseline results. In the baseline, the vehicles in GEM were divided to fulfill half of all mobility needs currently satisfied by cars through privately owned EVs, while the other half were fulfilled by a fleet of SAEVs. In one of the scenario analyses, researchers varied this assumption by altering the proportion of vehicles satisfying mobility demand via SAEVs from 0% to 100%.

Result

An aggregate view of SAEV behavior in the base scenario can be seen in Figure I.10.2, providing an overview of when vehicles are idle (green), moving (blue), or charging (red) across eight days of the year (representing two days in each season). The SAEVs are moving to pick up passengers, transport passengers, or drive to a charging station. The travel occurs primarily during the day, when individuals are headed to their destinations. Notably, we are able to observe two peak periods corresponding to the morning and evening commutes. During these peak periods, the SAEV fleet is nearly fully utilized, and we see that, at these times, almost all vehicles are either moving or charging. During nighttime hours, by contrast, most SAEVs are either idle or charging.

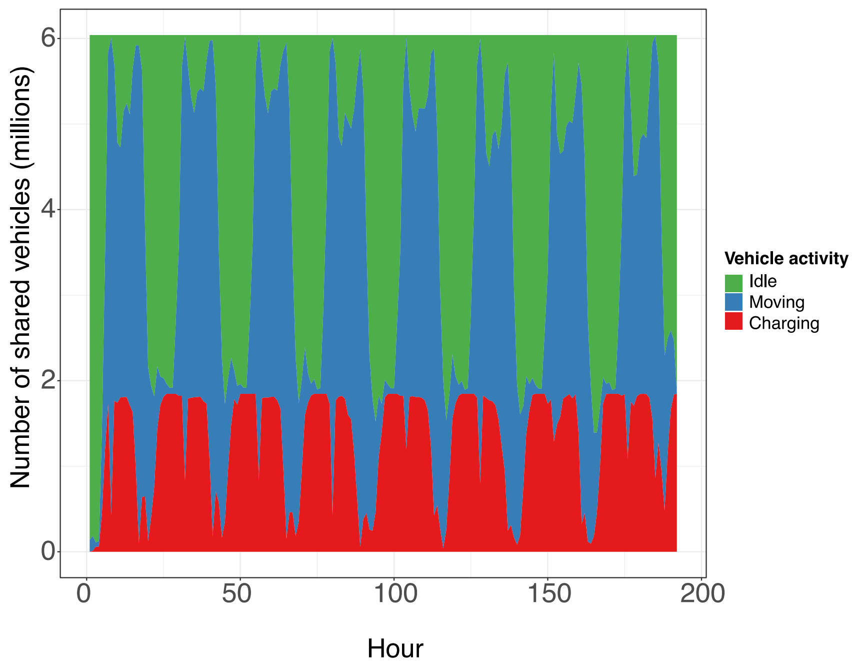

Figure I.10.2 Eight days of SAEV activity (two representative days in each season of the year) aggregated across the United States

Figure I.10.3 shows the charging profiles of both private EVs and the fleet of SAEVs across eight representative days on an hourly basis for the base scenario. The charging load for private EVs, in red, has a noticeably larger peak than the charging profile for SAEVs. The SAEVs charge in a "smarter" pattern than the private EVs because they consider the real-time cost of electricity. Despite the fact that both private EVs and fleet SAEVs satisfy half of the travel demand in the system, the energy requirements are different, with private EVs using 1.7 times more energy. Several factors contribute to this difference. The factors that reduce SAEV energy consumption are sharing (more mobility satisfied with fewer miles), vehicle efficiency, and charging efficiency. One factor that increases SAEV energy consumption is the increased deadheading that occurs when empty vehicles are driving to pick up passengers or to travel to charging stations (in our simulation this ranges from 5-30% of total SAEV vehicle miles), but this factor is outweighed by the aforementioned benefits. Results also indicate that the proportion of charging rates is not highly correlated with the time of day.

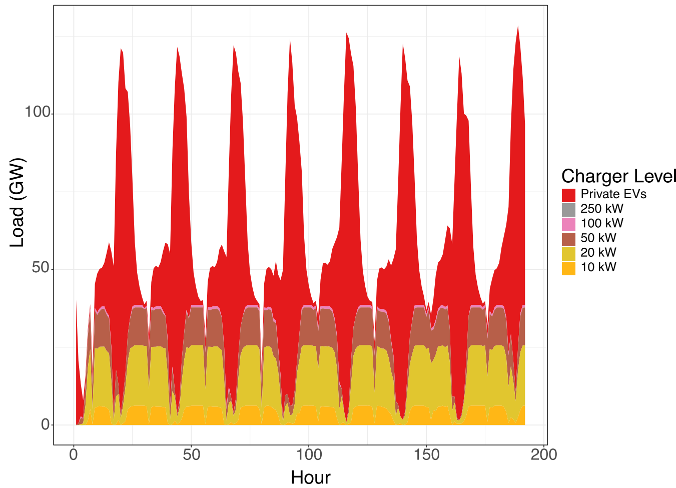

Figure I.10.3 Charging profile over eight days (two representative days in each season of the year) across the United States in the baseline scenario with SAEVs serving 50% of mobility needs

In the sensitivity analysis, researchers varied the portion of mobility served by SAEVs, revealing tremendous potential that fleet can have on the transportation system. Figure I.10.4 and Figure I.10.5 show that the composition of vehicles and chargers required to fulfill mobility with an SAEV fleet stands in stark contrast to doing the same with a personal EV fleet. When personal EVs serve 100% of light-duty mobility, approximately 150 million vehicles are required, yet the same mobility can be served with approximately 12 million SAEVs. The vast majority of trips are fulfilled by 75- and 150-mile-range vehicles, with a small portion of 225-mile-range vehicles serving longer-distance trips. This reduction in fleet size is possible because vehicle autonomy enables significantly higher utilization of any given vehicle; ride pooling is also a contributing factor.

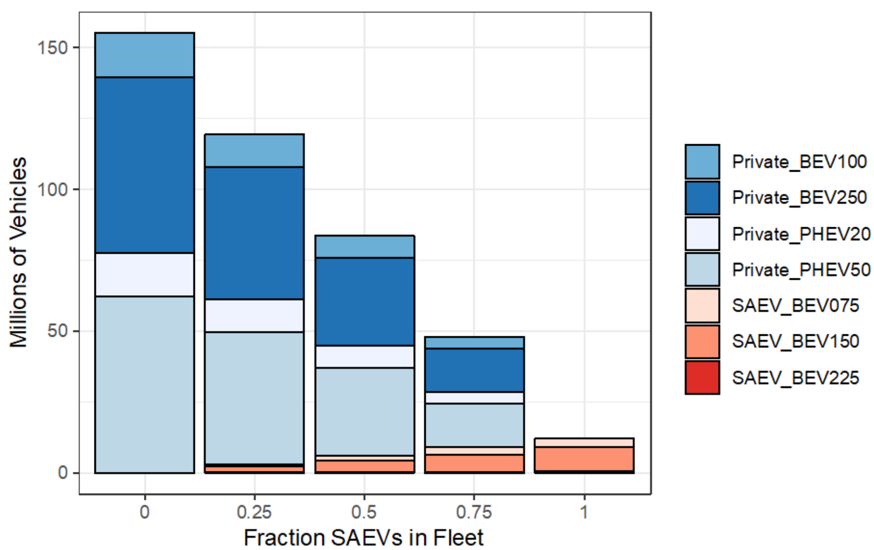

Figure I.10.4 Total number of private BEVs and SAEVs by battery range as SAEVs serve from 0% to 100% of mobility demand

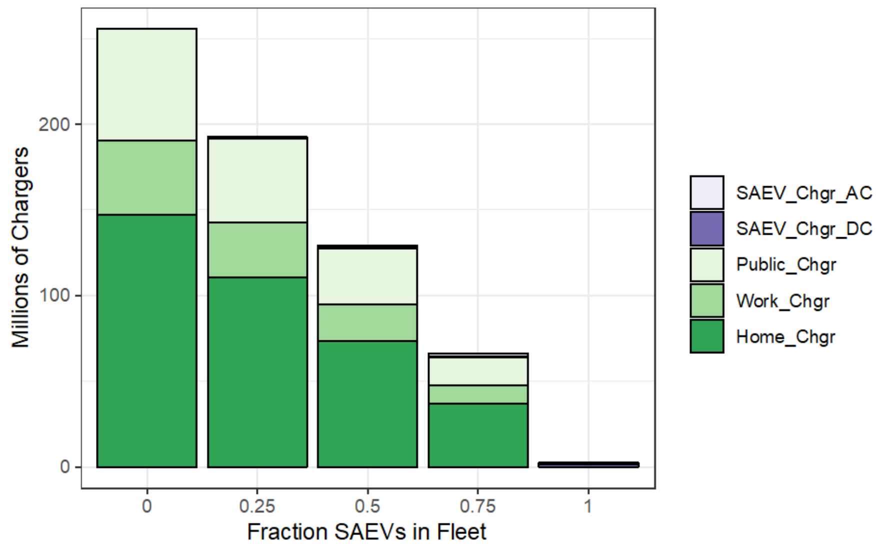

Figure I.10.5 Total number of chargers required to serve private BEVs and SAEVs as SAEVs serve from 0% to 100% of mobility demand

Likewise, for EV charging, less than 5 million individual chargers are needed to fulfill the requirements of a 100% SAEV fleet, compared to over 250 million for a personal EV fleet. These chargers consist primarily of lower power levels (20 kW or lower) but also include some 100 kW and 250 kW chargers. GEM is able to optimally dispatch its entire fleet of SAEVs to share chargers at significantly higher utilization rates than are seen at public chargers today—thus allowing a smaller number of chargers to fulfill vehicle demand.

In Figure I.10.6 and Figure I.10.7, we see that SAEV fleets can reduce peak load in the system by over 50% and the total cost of ownership by over 60%. The peak load reduction is achieved by virtue of the fact that the SAEV fleet schedules charging mostly evenly over the course of the day to avoid infrastructure costs, but also with some curtailment during the peak mobility hours and high-cost evening hours when the remainder of electric load is peaking.

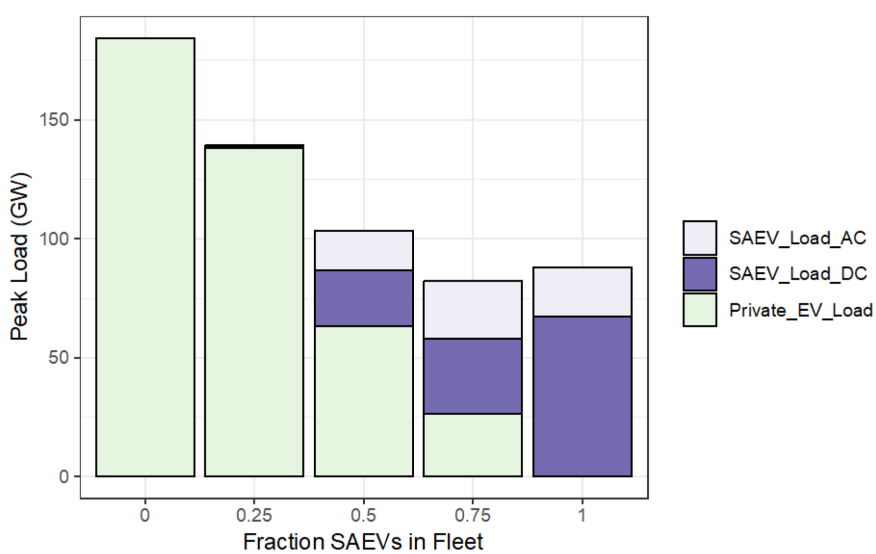

Figure I.10.6 Peak load from charging
as SAEVs serve from 0% to 100% of mobility demand

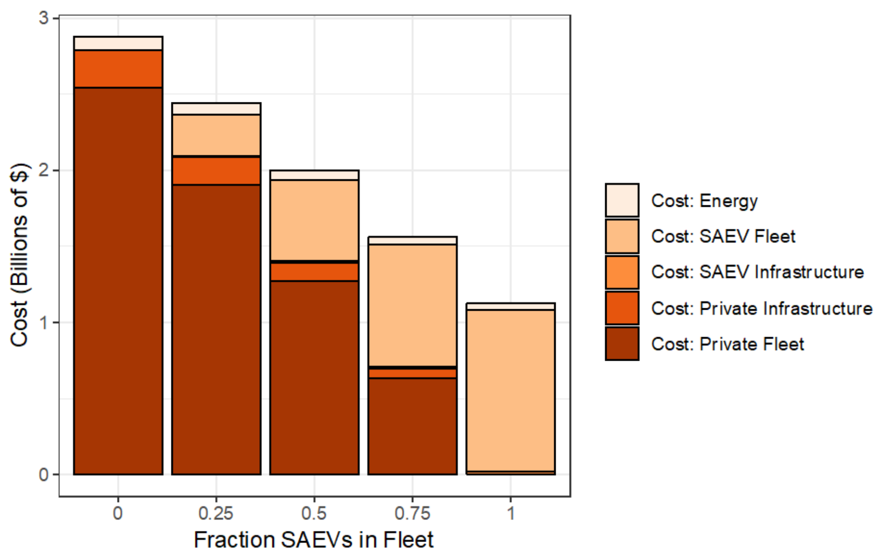

Figure I.10.7 Total cost of ownership
as SAEVs serve from 0% to 100% of mobility demand

Conclusions

The configuration of a mobility system in which SAEVs serve demand for trips has dramatic benefits over one that relies on personally owned EVs. Mobility is successfully fulfilled by a small fraction of the total number of vehicles on the road today, with a surprisingly small number of corresponding EV chargers. From an economic standpoint, system costs are significantly reduced through sharing and automation, while fuel and operations costs remain much lower than those of gasoline vehicles today. From a grid operations perspective, the SAEVs are able to smooth out large amounts of the variability in electricity generation, which would significantly improve both the efficiency and emissions rate of fossil generation while simultaneously better utilizing solar and wind resources (thanks to flexibility in charging times).

Key Publications

1. Sheppard, Colin J. R., Gordon S. Bauer, Brian F. Gerke, Jeffery B. Greenblatt, Alan T. Jenn, and Anand R. Gopal (2019). "Joint Optimization Scheme for the Planning and Operations of Shared Autonomous Electric Vehicle Fleets Serving Mobility on Demand." *Transportation Research Record*, April 13, 2019. 0361198119838270. https://doi.org/10.1177/0361198119838270.

2. Sheppard, Colin, Julia Szinai, Nikit Abhyankar, and Anand Gopal (2018). "Grid Impacts of Electric Vehicles and Managed Charging in California: Linking Agent-Based Electric Vehicle Charging with Power System Dispatch Models." Lawrence Berkeley National Laboratory, December 2018.

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I.11 Transportation Energy Evolution Modeling

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Project Introduction

Vehicle market dynamics modeling for energy transition issues is important to the U.S. Department of Energy (DOE) mission and to its stakeholders, as it improves understanding and enables quantifying the future value of research and development (R&D). Technology impacts (e.g., energy consumption, consumer costs, and energy security) are often used to justify and prioritize R&D investments in advanced vehicle technologies. Quantifying such impacts requires estimating consumer adoption of the technology. However, consumers may have views on technologies that differ from the perspectives of engineers, scientists, and economists. Meanwhile, suppliers seek less risk, more market certainty, and good public image, in addition to profits. These needs present challenges in understanding and modeling supplier behavior (e.g., product provision and pricing decisions) and the resulting technology acceptance of advanced vehicle technologies.

To alleviate these challenges, the Transportation Energy Evolution Modeling (TEEM) program from Oak Ridge National Laboratory (ORNL) developed the MA^{3}T (Market Acceptance of Advanced Automotive Technologies) model and its derivative models to simulate market penetration and dynamics in transition scenarios toward energy-efficient vehicle and mobility technologies in the highway sector. The MA^{3}T model's key output is annual sales shares of a vehicle or mobility technology (e.g., 42-volt mild hybrid, 200-mile battery electric vehicle (BEV), or autonomous shared mobility). Model inputs include consumer segmentation and attributes, technology cost and performance, infrastructure availability and prices, and government incentives. All these inputs can be easily changed, and model operation requires only installation of Microsoft Excel.

The success of the Vehicle Technologies Office (VTO) analysis investment in the MA^{3}T model has been evidenced by expanded sponsorship for both the model's application and its adaption for other purposes; sponsors include the International Institute for Applied Systems Analysis (IIASA), Aramco, VTO's Energy Efficient Mobility Systems program, the Fuel Cell Technologies Office, the Bioenergy Technologies Office, and the Office of Energy Efficiency and Renewable Energy. MA^{3}T was originally developed to focus on the light-duty vehicle market in the United States and was later adapted to other market–energy scenarios and expanded to other quantitative model tools: (1) MA^{3}T-CN (funded by Aramco), which simulates plug-in electric vehicle (PEV) market penetrations in China, (2) MA^{3}T-Global (initially funded by IIASA), which estimates transportation energy transitions in multiple vehicle markets from the perspective of globalization, (3) MA^{3}T-TruckChoice, which simulates market penetrations of powertrain technologies and energy uses of commercial fleet vehicles in the United States, and (4) MA^{3}T-MobilityChoice, which simulates market penetrations and synergies of electrification, automation, and shared mobility. Some of the work was funded by international organizations and the private sector. Currently, published applications of the model cover the topics of (1) compliance analysis 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 effects of vehicle automation on electrification, and (6) impacts of dynamic wireless charging on PEV sales.

Objectives

The TEEM/MA^{3}T project objectives are to (1) develop a user-friendly, useful, and credible simulation tool in support of technoeconomic analysis with respect to energy-relevant vehicle technologies; (2) close key knowledge gaps in fundamental issues for research (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 conduct quick-turnaround scenario analysis of interest to stakeholders.

Approach

The core of the MA^{3}T 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 feedback 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. Model inputs include consumer segmentation and attributes, technology cost and performance, infrastructure availability and prices, and government incentives.

The original MA^{3}T model was focused on choice of fuel types (e.g., conventional gasoline vehicles versus hybrid electric vehicles [HEVs] versus PEVs). One major component of the TEEM/MA^{3}T 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:

- Mobility – What if shared mobility eliminates first/last-mile inconvenience?
- Consumer – What if consumers demand a three-year payback?
- Technology – What if batteries cost $80/kWh by 2030, micro-hybrid vehicles become more market-competitive, or vehicle automation increases travel demand?
- Infrastructure – What if 100 kW fast-charging is strategically offered?

Investigating these assumptions and their impacts on technology acceptance of advanced vehicles is an important ongoing task for the team.

In particular, to improve the future MA^{3}T modeling assumptions, the team's primary efforts in fiscal year (FY) 2019 were to update and calibrate the MA^{3}T model with the most recent data sources and public literature, to capture the market dynamics affected by the development of charging infrastructure and related technologies, and to better understand transportation energy decisions under stochastic uncertainty and impacts of new technology trends such as micro/mild hybrid vehicles. The results section below highlights major findings of three studies conducted in FY 2019.

Results

Impacts of the consumer heterogeneity in fuel economy valuation

In a paper published in *Energy*, the research team quantified the significance of assuming heterogeneity in consumer valuation of fuel economy on the estimated compliance with fuel economy standards. The researchers used two approaches: mathematical derivation on how heterogeneity affects the estimated market acceptance of high-efficiency vehicles, and a consumer choice-based simulation method to analyze the heterogeneity impacts on the compliance with the fuel economy standards for the entire light-duty vehicle fleet in the United States. The findings suggest that the direction of the impact of heterogeneity assumption depends on market positions of high-efficiency vehicles (1) with the "Likely-Accept" condition, in which high-efficiency vehicles sell well and higher fuel economy is expected, the heterogeneity assumption can add additional risks to the compliance; and (2) with the "Likely-Reject" condition, in which the fuel economy standards may have difficulty in compliance, the heterogeneity can reduce the risks and improve the compliance outcome. Consideration of fuel economy valuation heterogeneity is important in fuel economy standard analysis, and such consideration may provide a framework to reconcile the different views on consumer valuation of fuel economy.

How different oil price conditions affect the heterogeneity impacts on the estimated Corporate Average Fuel Economy (CAFE) compliance is investigated, and the "BaseValue" scenarios are shown in Figure I.11.1 as an example. Three different oil price projections (reference oil prices [RefOil], low oil prices, and high oil prices) are simulated in the "BaseValue" scenario. The oil price projections are based on the 2016 Annual Energy Outlook. The high oil price projection (HighOil) has a continuous high oil price environment. That strengthens the "Likely-Accept" condition for high-efficiency vehicles. Therefore, the reduction in the estimated achieved fuel economy is magnified when the heterogeneity is present, reaching 1 mpg by 2025. On the other hand, the low oil price projection (LowOil) weakens the "Likely-Accept" condition for the "BaseValue" scenario and amplifies the "Likely-Reject"condition. Therefore, heterogeneity contributes to an increase in the estimated achieved fuel economy in later years.

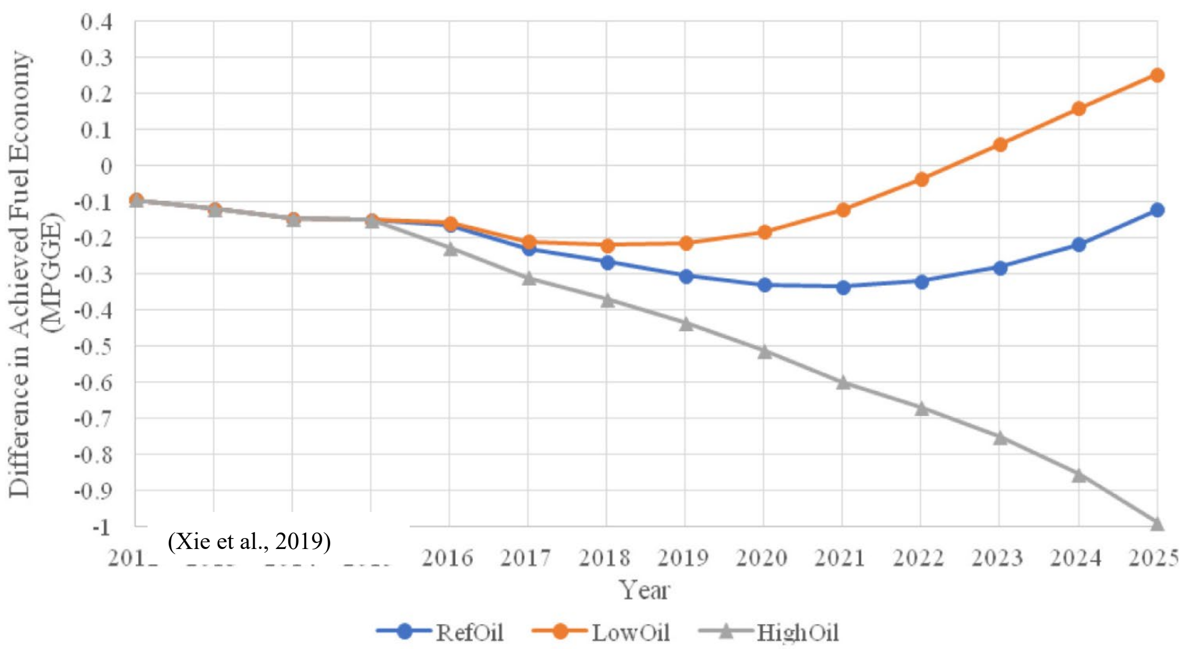


Figure I.11.1 Relative changes in estimated CAFE achieved fuel economy ("BaseValue" scenario)

Hybrid technologies' impacts on vehicle market fuel economy and electrification

ORNL and Argonne National Laboratory (Argonne) jointly conducted analysis of market penetrations of micro HEVs. Argonne focused on literature review of past market development, performance, incremental costs, and third-party projections, and ORNL focused on simulating market penetrations of micro HEVs using the new MA^3T model version released in 2019. This study was dedicated to evaluating the impacts of the M-HEV technology (micro-hybrid electric vehicles and mild-hybrid electric vehicles) on the U.S. vehicle market from the perspective of vehicle sales, industry average fuel economy, and relations with PEVs. Compared to prior research, one major contribution of this study was to quantify the competitiveness of hybrid technology in the context of dynamic improvement of electrified and fuel-saving powertrain technologies. This result was achieved by integrating fuel economies and production costs into the MA^3T model.

The research team examined the role of low levels of electrification, namely micro and mild hybridization (jointly labeled as M-HEV), on improving fuel economy of internal combustion engine vehicles. Reviewing recent literature and data sources provided the estimates of the M-HEV technology's manufacturing cost and fuel economy. By adopting the most recent released MA^3T model, the research team projected the market penetration of the M-HEV technology under different scenarios that depend on how the M-HEVs are classified in different technology segments. It was found that these vehicles are likely to improve fleet average fuel economy without significant adverse effects on sales of vehicles with electric powertrains, and that these hybrids are likely to dominate the conventional vehicle market share by 2050. Improvement of vehicle fuel economy with limited extra costs assists market penetration of the M-HEVs, and the adoption of M-HEV technology might be beneficial to the industry. However, the simulation also showed that the overall fuel economy in conventional vehicles might fall a bit when all M-HEVs are classified as non-hybrid vehicles, since the growth of M-HEV sales could cannibalize the HEV market and narrow the HEVs' contributions to overall fuel economy.

As shown in Figure I.11.2, the market share of M-HEV technology varies if the M-HEV technologies are classified into different vehicle segments. Scenario (a) has no M-HEV technology considered, and it works as a comparison. In Scenario (b), in which M-HEV technology is classified as conventional internal combustion engine (ICE) vehicles, the market share of M-HEV technology, specifically the micro-HEVs, grows markedly; however, the sales share of conventional ICE vehicles shrinks rapidly while the sales of full-hybrid HEVs are largely unchanged compared with the sales in the Scenario (a). Similarly, the M-HEV technology will largely affect the shares of conventional ICE vehicles and full hybrid HEVs in Scenarios (c) and (d), no matter how the M-HEVs are classified. The conventional ICE vehicles will face a great challenge from the M-HEVs, which have better fuel-efficient technologies with an acceptable increase of manufacturing costs. However, as presented by the four scenarios in Figure I.11.2, M-HEV technology in general has far less impact on the market shares of BEVs and plug-in hybrid electric vehicles. In the short term (before year 2025), M-HEVs will be soon popularized in the vehicle market and muffle the momentum of PEV market growth to some extent. Meanwhile, the vast majority of M-HEV sales are contributed by micro-HEVs, no matter how the M-HEV is classified in the vehicle segments. This might be because of the vague position of mild-HEV: on the one hand, it integrates many new technologies to improve the fuel economy; on the other hand, it is still regarded as an upgrade product from the ICE vehicle.

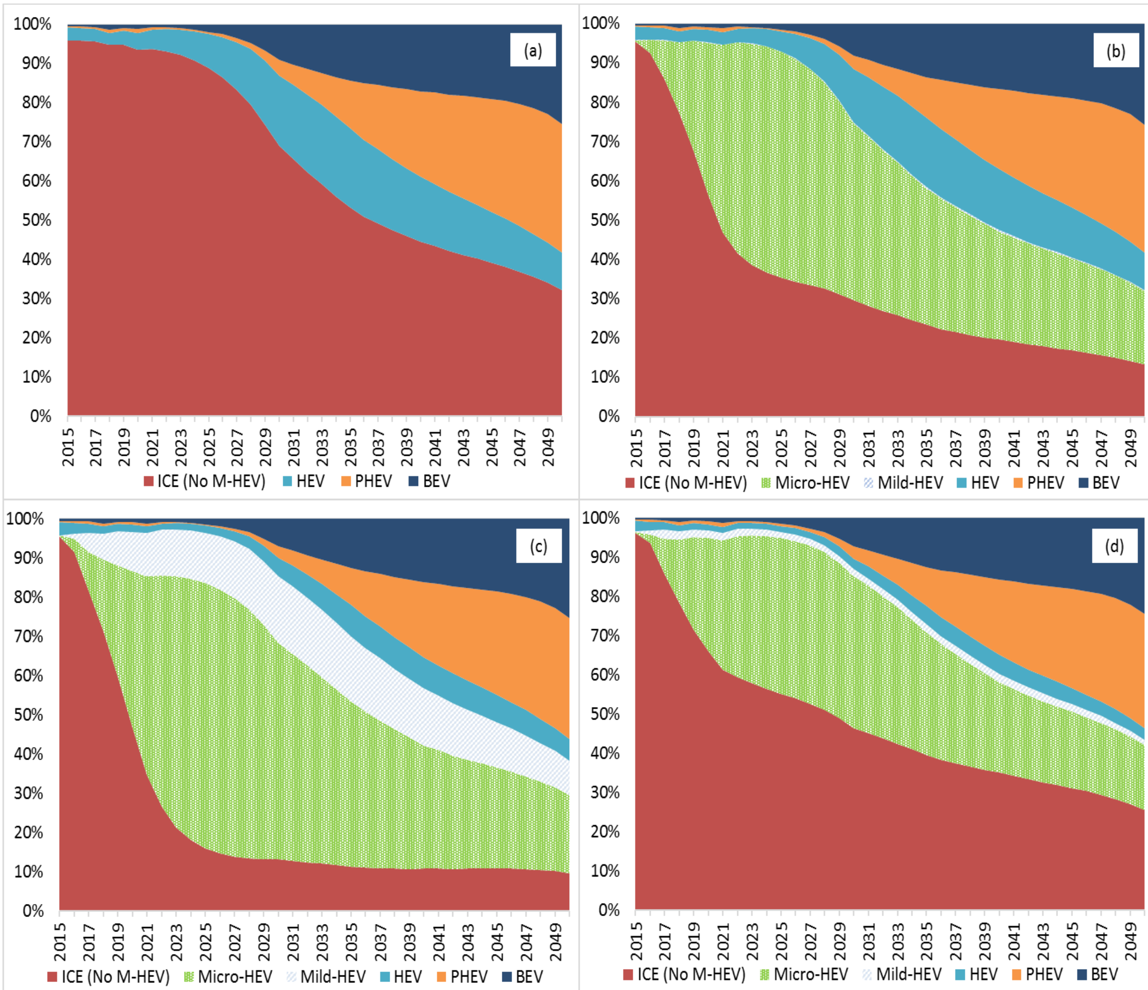
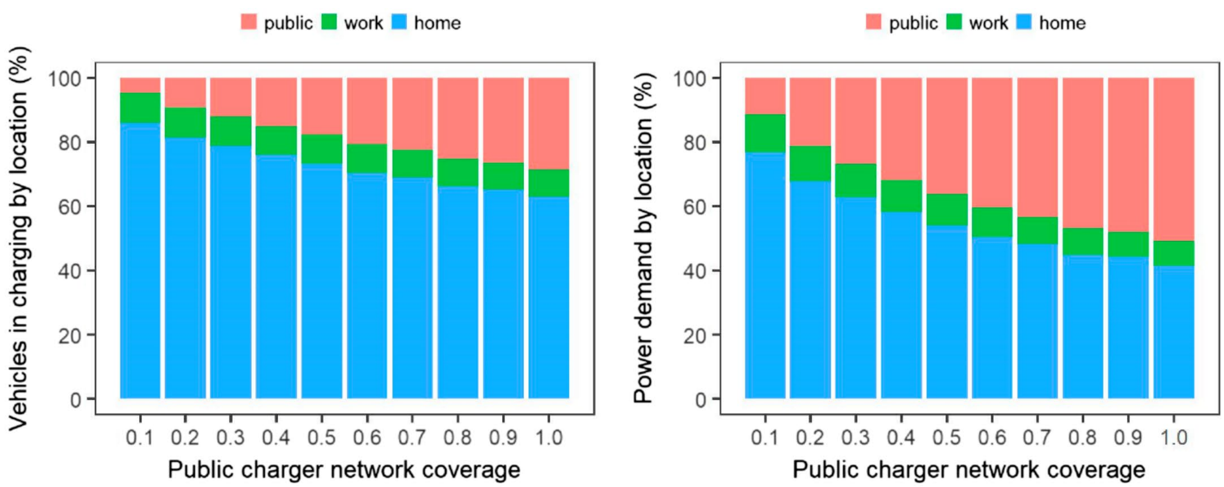


Figure I.11.2 Projection of the vehicle market share using the MA^{3}T model: (a) no M-HEV technology; (b) with both M-HEVs regarded as conventional ICE vehicles; (c) with micro-HEVs regarded as conventional ICE vehicles and mild-HEVs regarded as HEVs; and (d) with both M-HEVs regarded as HEVs (Hu et al., 2019)

Charging behavior of battery electric vehicle drivers

This study focused on drivers' behavior in terms of charging BEVs. BEV drivers can be influenced by psychological factors such as personality and risk preference. The research team proposed a cumulative prospect theory (CPT)-based modeling framework to describe BEV drivers' charging behavior. CPT captures an individual's attitude and preference toward risk in the decision-making process. A BEV mass market scenario was constructed using 2017 National Household Travel Survey data. The research team applied the CPT-based charging behavior model to study the battery state of charge (SOC) when drivers decide to charge their vehicles, charging timing and location choices (as shown in Figure I.1.3), and the charging power demand profile under the mass market scenario. BEV drivers who display a higher degree of risk-seeking tend to charge vehicles at a lower SOC. Some home charging shifts to workplace and public charging as the public charger network expands, but home charging still plays the most significant role in BEV use. The power demand from public chargers increases significantly with BEV expansion and has a larger impact on the power grid. The time-of-use electricity rate can shift peak power demand to off-peak periods from midnight to early morning.

Figure I.11.3 shows how public charger coverage[9] affects charging location choices and power demand. As public charger coverage increases, drivers are more likely to use public chargers. About 20% of vehicles charge at public locations when the charger coverage exceeds 0.6. However, home charging still plays the dominant role and accounts for 63% of all charging events, even if public charging opportunities are readily available.



(a) Impact on charging location (b) Impact on charging power demand

Figure I.11.3 Impacts of public charger network coverage on charging location and charging power demand (Xie et al., 2019)

Dynamic wireless charging technology for battery electric vehicles

ORNL and University of Michigan jointly conducted a life cycle assessment of dynamic wireless power technology (DWPT) to assess the sustainability performance of DWPT applied in a network of highways and urban roads for charging electric passenger vehicles. The related paper has been published in *Transportation Research Part C: Emerging Technologies*.

The assessment compares DWPT to stationary wireless charging and to conventional plug-in charging using a case study of Washtenaw County, Michigan, over 20 years. The life cycle assessment is based on three key sustainability metrics: costs, greenhouse gas (GHG) emissions, and energy use, encompassing not only the use-phase burdens from electricity and fuel, but also the upfront deployment burdens of DWPT infrastructure. Research results indicate that optimal deployment of DWPT, electrifying up to about 3% of total roadway lane-miles, reduces life cycle energy by up to 6.8%, and enables downsizing of BEV battery capacity by up to 48% compared to the non-DWPT scenarios. Roadside solar panels and storage batteries are essential to reducing life cycle energy burdens significantly, but these technologies bring additional costs. Analysis indicates that breakeven for solar charging benefits to pay back the DWPT infrastructure burdens can be less than 20 years for energy burdens but more than 20 years for costs. A roadway segment with volume greater than about 26,000 vehicle counts per day, speed slower than 55 miles per hour (1 mile ≈ 1.609 km), and pavement remaining service life shorter than 3 years should be prioritized for early-stage DWPT deployment.

The project conducted a sensitivity analysis to evaluate the effects of the annual budget constraint on optimal DWPT deployment and coverage growth and the resulting electric vehicle (EV) market share increase; results are shown in Figure I.11.4. The annual budget in the base case is $30 million/year. On one hand, an annual budget lower than $15 million/year is found to significantly decelerate DWPT coverage and BEV market share growth. On the other hand, an annual budget beyond $30 million/year would not significantly change the

[9] Public charger coverage is defined as the probability that a charger is available at trip destinations.

curves of DWPT coverage and BEV market share growth, indicating that an annual budget of $30 million/year is sufficient.

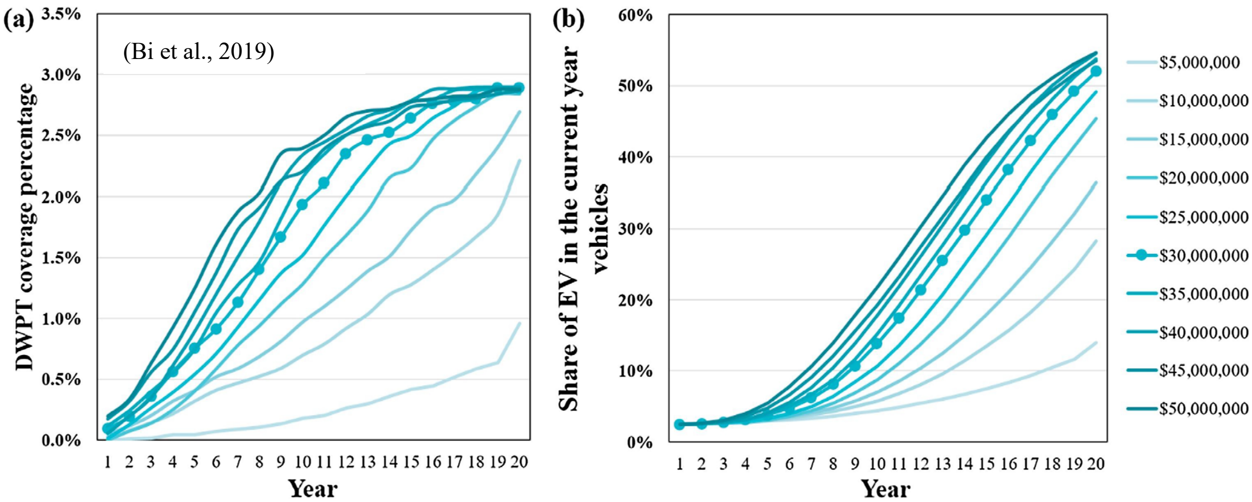


Figure I.11.4 Sensitivity analysis of annual budget for deployment of dynamic wireless charging infrastructure, with a base case annual budget of $30 million/year

Optimizing workplace charging facility deployment

The research team built a workplace charging optimization model that could help service providers (i.e., companies) with workplace charging planning to maximize electric miles of employee PEVs with a given budget. In addition to the planning decisions on workplace charging station setup and charger selection, the model specifically optimizes detailed workplace charging operations on charging spot assignment and charging schedule, considering temporal distribution of charging demands and varied electricity price. Results of experiments based on national average travel data indicate that the actual workplace charging strategy varies with budget level, and through optimization, the strategy could effectively reduce impacts of varied electricity prices with smart charging, namely, shifting charging schedules to periods when electricity prices are low. Also, with an alternative version of the model, the research team further investigated the tradeoff between workplace charging and home charging with a subsidy. The researchers observed that their relative competitiveness depends mainly on the actual home charging subsidy level, which could vary by geographic location.

Figure I.11.5(a) plots the total unsatisfied charging demand in electric miles, and the results show a clear decreasing pattern of unsatisfied electric miles with increases in the budget. When the annual budget below $25,000, the majority (>50%) of electric mile demand could not be satisfied by workplace charging; when the budget reaches $75,000, all electric mile demand is served. Figure I.11.5(b) depicts the under-served demand in terms of the number of PEVs either completely uncharged or partially charged (meaning that the PEV has partial charging demand fulfilled) under different budget levels. When the budget is low, most PEVs could not be fully served by workplace charging. At the $10,000 annual budget level, only 1 out of all 100 PEVs could be fully charged to the required demand, while 7 PEVs receive partial charging, and the remaining 92 PEVs do not receive the charging service at all. However, when the budget increases, there is significant reduction in the number of under-served and uncharged PEVs.

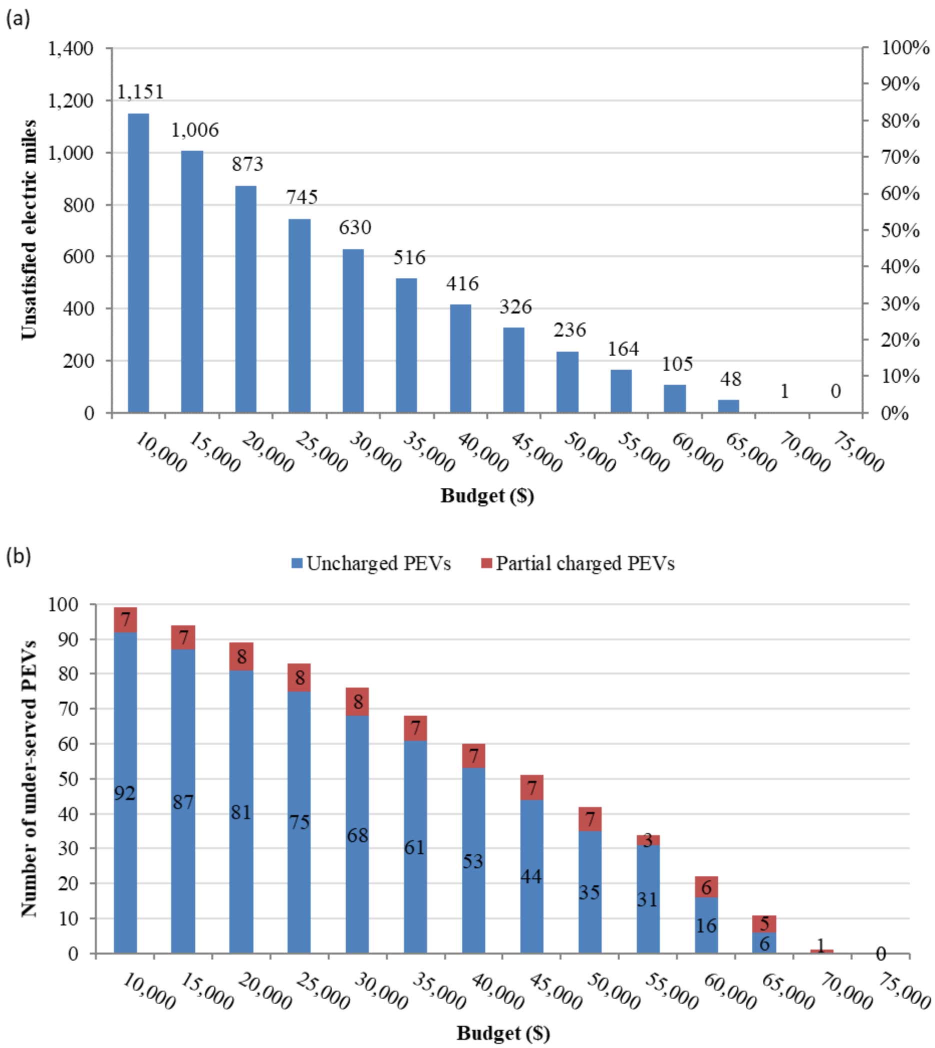


Figure I.11.5 Unsatisfied demand with flat electricity price at different budget levels: (a) unsatisfied demand in electric miles and (b) under-served PEV demand

Conclusions

In FY 2019, the project conducted research on vehicle-technology-related topics to investigate potential extensions of the MA^{3}T model and identify opportunities to improve the existing assumptions within the MA^{3}T model. Results from the paper on BEV drivers' charging behavior can improve the assumptions in the consumer segment of the MA^{3}T model. In addition, two studies on charging infrastructure—the life cycle assessment of wireless charging and the study of charging stations and pricing—could enable the future MA^{3}T model to model linkage of advanced charging infrastructure support and technology acceptance of BEVs. Continuous improvement of the MA^{3}T model can be adopted to evaluate the impacts of consumer heterogeneity on the fuel economy and to study market penetration of micro-HEV technologies.

During FY 2019, the project team published 12 peer-reviewed journal papers and one book chapter. Several manuscripts are currently under review for journal publication.

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I.12 ParaChoice Model

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Project Funding: $1,330,000 DOE Share: $1,330,000 Non-DOE Share: $0

Project Introduction

Sandia National Laboratories' Parametric Choice Model (ParaChoice) supports the U.S. Department of Energy Vehicle Technologies Office mission. Using early-stage research as input, ParaChoice supports the informed development of technology that will improve affordability of transportation, while encouraging innovation and reducing dependence on petroleum. Analysis with ParaChoice enables exploration of key factors that influence consumer choice, as well as projecting the effects of technology, fuel, and infrastructure development for the vehicle fleet mix. Because of the distinct differences between requirements, needs, and use patterns for light-duty vehicles (LDVs) relative to heavy-duty vehicles (HDVs), this project separately models the dynamics of each of these segments to accurately characterize the factors that influence technology adoption.

Objectives

The overall project objective is to assess the evolving integration potential of LDV and HDV technologies, fuels, and infrastructure and their contributions to lowering emissions and petroleum consumption. The project team leverages existing LDV and builds HDV ParaChoice capability to conduct parametric analyses that explore the trade space for key factors that influence consumer choice and technology, fuel, and infrastructure development. ParaChoice provides the unique capability to examine tipping points and tradeoffs, and can help quantify the effects of and mitigate uncertainty introduced by data sources and assumptions.

LDV analysis goal: Determine the potential for alternative fuel LDVs to penetrate the market, reduce LDV petroleum consumption and emissions, and affect energy use for two scenarios to support the benefits analysis low and high technology cases.

HDV analysis goal: Provide the capability to model plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and fuel cell electric vehicles (FCEVs) to reflect the changing technology space for HDVs, and evaluate the potential for alternative fuel heavy-duty vehicles (AFHDVs) to penetrate the market, increase freight hauling efficiency, and reduce pollution.

Approach

ParaChoice is a system dynamics model incorporating energy sources, fuels, and LDVs or HDVs; see Figure I.12.1. Simulations begin with today's energy, fuel, and vehicle stock and project 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 (Levinson et al. 2016; Barter et al. 2012).

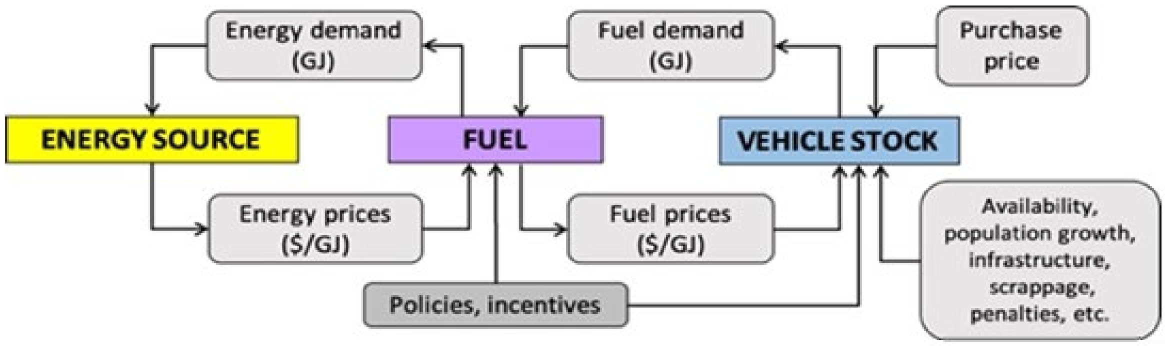

Figure I.12.1 Schematic of ParaChoice systems dynamices model structure that indicates how energy, fuel, and vehicle stock affect each other iteratively. The model allows for incentives and policy options to act as functions of time.

ParaChoice is designed to enable parameterization that can be used to explore uncertainty and trade spaces, allowing identification of tipping points and system sensitivities. Uncertainty analyses include trade space analyses in which two parameters are varied, generating hundreds of scenarios, and sensitivity analyses in which many parameters are varied at once, generating thousands of scenarios. Parameter ranges are selected to explore plausible and "what if" regimes and provide thorough coverage of possible future states. Analysis products using ParaChoice provide insights into (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.

Vehicles, fuels, and populations are segmented to study the competition between powertrains and market niches; see Figure I.12.2. Baseline inputs into the ParaChoice model include the following data and modeling sources:

- GREET 2016 (Argonne 2016): emissions & fuel cost
- National Household Travel Survey (National Highway Traffic Safety Administration [NHTSA] 2006): LDV fleet segmentation
- Polk (IHS n.d.): HDV fleet segmentation and price projections
- Autonomie Vehicle System Simulation Tool 2018 (Argonne 2018): fuel efficiency, PEV charge depleting (CD) range, price projections
- Alternative Fuel Data Center (DOE n.d.): 2010–2017 fueling stations and policies by state
- Vehicle Inventory and Use Survey (U.S. Census Bureau 2002): vehicle ton-mile travelled (VTMT)
- Public Transportation Fact Book (American Public Transportation Association 2019): VTMT
- Freight Analysis Framework V4 (ORNL 2018): VTMT
- Advancing Technology for America's Transportation Future (National Petroleum Council [NPC] 2012): efficiency
- Final Rule for Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles – Phase 2 (U.S. Environmental Protection Agency [EPA] 2016): efficiency
- Annual Energy Outlook (Energy Information Administration 2018): fuel costs

- Hydrogen Delivery Scenario Analysis Model (Argonne 2015): fuel costs
- H2A (National Renewable Energy Laboratory 2015): fuel costs
- Foothill Transit Agency (2018): price projections
- International Council on Clean Transportation (2017): price projections

Results

In fiscal year (FY) 2019, the project added three alternative fuel powertrains to the ParaChoice Truck (HDV) model—BEV, PHEV, and FCEV—and demonstrated the capability for a subset of the HDV segment. Results from the LDV analysis supporting the benefits analysis will be published in FY 2020 (owing to delays in receiving the inputs before the end of the fiscal year).

To inform HDV model development and which vehicle segment to demonstrate this year, the project conducted a gap analysis that incorporates an in-depth literature review to determine whether data are available and sufficient to answer specific analysis questions. The team used a multistep process, beginning with identifying relevant analysis questions that can be addressed using ParaChoice: the associated data needed; the data availability and quality; and given the quality, what questions of interest can be credibly pursued. The analysis identified (1) specific data gaps that limit the vehicle types and powertrains that can be studied in the near term; (2) specific data gaps around HDV consumers that create uncertainty in projections; and (3) inconsistencies in data aggregation across vehicle types, weights, powertrains, duty cycles, and vocations that may introduce further uncertainty into the analysis results.

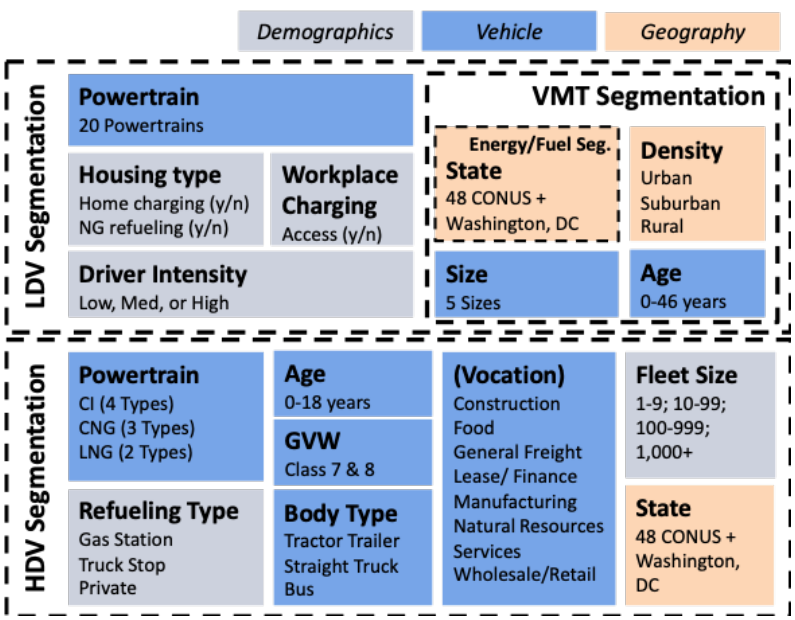

Figure I.12.2 LDV and HDV segmentations grouped into themes of buyer demographics (e.g., access to workplace charging or truck stop versus gas station refueling), vehicle options (e.g., powertrain or body type), and geography (e.g., state or population density)

The project's FY 2018 market segmentation analysis indicated tractor trucks comprise almost half of Classes 7 and 8 HDVs, travel approximately three-quarters of the total annual miles, and consume three-quarters of the fuel. Based on those results and the gap analysis, the research team selected long haul tractor trucks to demonstrate the ParaChoice Truck modeling capability this fiscal year. This segment was primarily based on the combination of Polk and VIUS segmentation, described as follows (items in parentheses are labels utilized in each data source):

- VIUS
  - “Tractor” entries under “TRUCKTYPE” category, across “CAB” category except for “half_cab” and “unknown” entries
  - “101 to 200 miles”, “201 to 500 miles” and “501 miles or more” entries under “TRIP_PRIMARY” label
- Polk
  - “Tractor_Truck” entries under “VEHICLE_TYPE” category

The Parachoice Truck modeling capability built on previous work (Askin et al. 2015) to provide choice among the following powertrains, with nesting according to fuel types (Figure I.12.3): compression ignition diesel (CI), mild-hybrid CI integrated start generator (CI-ISG), hybrid CI (CI-HE), compressed natural gas (CNG), hybrid CNG (CNG-HE), liquified natural gas (LNG), battery electric (BE), plug-in hybrid CI (CI-PHE), plug-in hybrid CNG (CNG-PHE), and fuel cell (FC). Note that BEVs and PHEVs fall under the plug-in electric (PEV) category and will be referred to as such in the subsequent sections of this report.

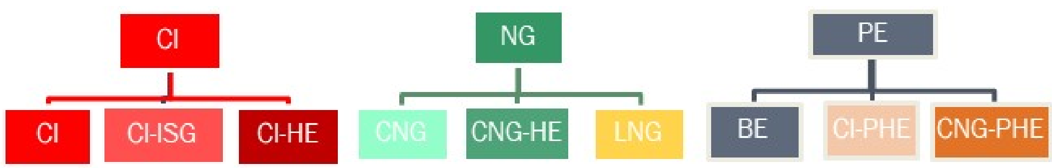

Figure I.12.3 Nesting method for HDV vehicles, added in conjunction with the addition of BEVs, PHEVs, and FCEVs

Because of variability in data values from different sources, as well as the finding that not all sources had data for all the powertrains of interest, some adjustments to the data were needed for use in the model. For example, fuel efficiency data from Autonomie are slightly different than those from EPA-NHTSA, and the NPC provides natural gas vehicle efficiencies while Autonomie does not. To minimize data error, these sources were normalized to one source by applying relative proportions derived from one source to another; e.g., the relative efficiency of CNG vs CI was derived from the NPC and applied to CI efficiency from Autonomie. As more refined data become available and are added to the model, specific results from projections will become more valuable. The addition of more single-source data and recent vehicle stock would further mitigate errors and allow for model calibration.

The baseline analysis for low technology and high technology cases (as defined by Argonne/Autonomie) show that there is negligible adoption of AFHDVs out to 2050. Figure I.12.4 shows the population of long haul tractor trucks by powertrain out to 2050, with fleet stock represented mainly by CI, NG, and their hybrids. Based on the model cost and efficiency input trends, CNG and CNG-HE appear to reach cost parity with CI around the year 2030 and begin to take a significant share of the vehicle stock. Comparison of the low and high technology cases suggests improved penetration of CI-HE, but AFHDVs continue to comprise only a small fraction of the fleet.

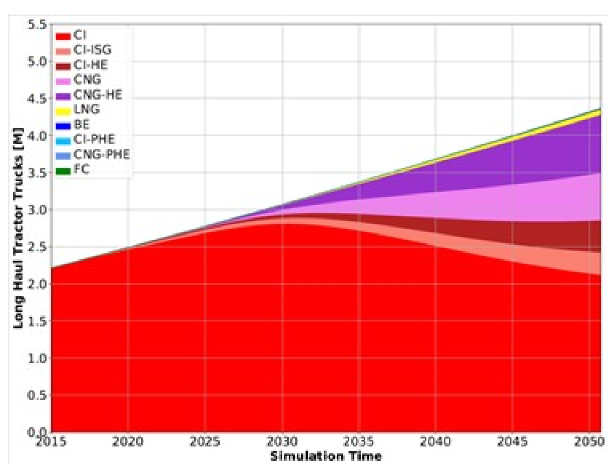

Figure I.12.4 ParaChoice projections of long haul tractor truck stock for the (a) low technology and (b) high technology case scenarios identified by Argonne/Autonomie

To understand what factors are suppressing adoption of the alternative powertrains, a sensitivity study using 2560 Monte Carlo samples (latin hypercube method) was conducted across input parameters. The results indicate carbon cost, acting as a cost modifier due to greenhouse gas (GHG) emissions, is the most impactful factor across all powertrains and should be viewed as a potential instrument for promoting AFHDVs with less GHG emission intensity than diesel.

For AFHDVs, FCEV and PEV purchase costs are the driving factor for adoption, suggesting purchase incentives and/or further cost reductions are needed to spur adoption of AFHDVs. In Figure I.12.5, AFHDVs at the current purchase point (yellow diamond) rest at a valley where CI, NG, and their hybrid counterparts dominate. Significant movement towards the left (lower PE costs) and the bottom (lower FC costs) of graphs are needed for FCEVs and PEVs to be competitive in the market. There are clear cost tipping points for these vehicles: ~$150,000 for FCEVs and ~$180,000 for PEVs (2018 dollar value). Below these points, FCEVs and PEVs begin to compete among one another (lower left corners in Figure I.12.5). The lower cost requirement for FCEVs is attributed to a cost of hydrogen per unit energy higher than electricity and FCEV efficiency per unit energy lower than PEVs. As a point of comparison, the modeled cost for CI at 2050 is $130,000. While less significant than purchase cost, marginal infrastructure cost (fueling and fuel production are endogenously built out in Parachoice) also contribute to limiting the adoption of AFHDVs.

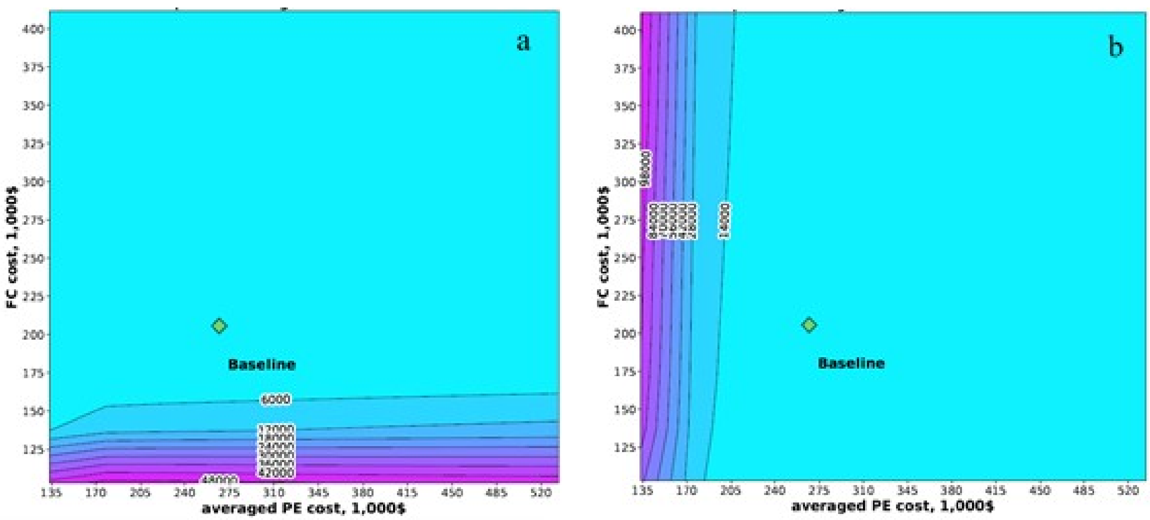

Figure I.12.5 Trade space analysis showing the number of (a) FCEVs and (b) PEVs at the end of analysis period (2050).The diamond marker notes baseline conditions.

Below are key findings from the long haul tractor truck analysis:

- AFHDVs have a negligible effect on the sales fraction of conventional CI powertrains projected to 2050. Adoption of AFHDVs is closely tied to the initial purchase cost of the vehicle. There is an apparent tipping point for adoption of these vehicles between $150,000 and $180,000. Incentive and financing options may be needed to promote adoption of these vehicles.
- NG vehicles appear to significantly displace conventional powertrains, as driven by lower purchase costs and lower fuel costs relative to the AFHDVs. They appear to readily compete in the baseline case; thus investments should target the alternative fuel powertrains.

Conclusions

ParaChoice is a 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. The model 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. Acquisition of more recent vehicle and VMT data are needed for further ParaChoice Truck model refinement. Incorporation of additional efficiency and cost data covering relevant permutations of tractor trucks, box trucks, buses, and vocational vehicles is planned for FY 2020.

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I.13 Transportation Segmentation Analysis

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Start Date: October 2017 End Date: December 2019
Project Funding (FY19): $300,000 DOE Share: $300,000 Non-DOE Share: $0

Project Introduction

The U.S. transportation sector is responsible for 28% of total energy use and 69% of total U.S. petroleum consumption (EIA 2019; Davis et al. 2019). Almost 15 million barrels of petroleum are used every day to move people and goods across the country (EIA 2019; Davis et al. 2019). While petroleum fuels have unquestionably provided reliable and convenient mobility options to power the modern global economy, they have also created challenges associated with geopolitics, energy security, price volatility, and environmental impacts.

Several fuels have been proposed as alternatives to petroleum products, and while today's U.S. transportation is still dependent on petroleum for 92% of its energy use (EIA 2019; Davis et al. 2019), several scenarios are projecting a major role for alternative fuels in the future. In particular, multiple alternative fuel vehicles and powertrains have been proposed, including hybrid electric vehicles, compressed natural gas (CNG) vehicles, liquefied petroleum gas vehicles, battery electric vehicles (BEVs), plug-in hybrid electric vehicles, hydrogen fuel cell electric vehicles (FCEVs), and a number of different biofuels for internal combustion engines. Each powertrain has different characteristics in terms of performance, capital and fuel costs, range, fueling/charging speed and availability, and consumer acceptance.

While many alternative options are currently available or soon to be available in the marketplace, there is still limited understanding of which technology might best serve as an alternative to incumbent gasoline and diesel vehicles. To complicate the matter, the transportation sector is heterogeneous and can be seen as divided into different "market segments." These market segments are characterized by different vehicle sizing and performance requirements to serve different purposes or applications, different use cases, and different annual vehicle miles traveled (VMT). For example, although a delivery truck and a service truck (such as a construction truck) belong to the same weight class, they have different performance requirements. Even vehicles that are similar in size and performance can be driven for significantly different mileages, leading to wide variations in applicability and affordability of different alternatives. For example, about 30% of single-unit trucks are driven for less than 15,000 miles annually, but vehicles in the top 30% of the single-unit truck VMT distribution are driven for over 30,000 miles annually (Davis et al. 2019).

Furthermore, alternative fuel availability and prices can vary significantly across different areas of the United States, leading to further differences in the optimal vehicle for a given purpose. For example, while the national average gasoline price in 2017 was $2.40 per gallon, South Carolina had the lowest gasoline price ($2.13 per gallon), whereas Hawaii had the highest ($3.09 per gallon) (DOE 2019). Similarly, the average residential electricity price in the United States was 10.3 cents per kWh, but residents of Louisiana paid 7.5 cents per kWh, and those in Hawaii paid 24 cents per kWh (EIA n.d.). This leads to significant differences when looking at least-cost options in different regions.

Objectives

Transportation energy use is complex and segmented, spanning multiple modes. Each of these modes requires vehicles with specific characteristics to satisfy range, power, and other vocational requirements, leading to a variety of market "segments." Different technologies can provide least-cost transportation services for different passenger and freight segments, based on technology and fuel costs, vehicle specification and use, and financial assumptions. At the request of the U.S. Department of Energy (DOE) Office of Energy Efficiency and Renewable Energy's (EERE's) transportation program offices (Vehicle Technologies Office, Fuel Cells Technologies Office, and Bioenergy Technologies Office), this project analyzes the opportunity for different technology use across multiple transportation segments and develops tools and visualizations to inform a strategic understanding of cost, energy use, emissions, and other metrics by transportation segment. In particular, the project provides the program offices with a dynamic tool to quickly assess these metrics in each segment by varying different parameters related to technological progress, economic variables, and behavioral assumptions.

Approach

This project takes a comprehensive view of transportation, and scope includes multiple subsectors (e.g., light-duty vehicles, medium- and heavy-duty vehicles, etc.), both today and estimated into the future. The researchers employ a unified methodology to identify which powertrain has the potential to be the "best" solution (in terms of a given metric) in a respective market segment and assess what technological development is necessary for different technologies to gain footholds in different segments. In particular, the project compares a variety of powertrains and fuel alternatives based on levelized cost of driving (LCOD) as a decision metric. In this study, LCOD incorporates capital costs of vehicle purchases and operational costs over a user-defined lifetime. The initial capital costs take into consideration different technology costs, at the component level, as well as the component sizing requirements in each segment. The operational costs take into account fuel costs, variability in miles driven across the market segments, and fuel economies of each powertrain, as well as including the capability to include other vehicle costs such as maintenance and insurance, pending data availability. Additionally, it is important to understand that a consumer's decision does not always depend on cost only; several other factors play a key role in determining technology adoption: driving experience and consumer preference for different alternatives, convenience of fueling (e.g., the locations where vehicles can be charged or filled, the time that it takes to charge or fill, and the frequency at which a vehicle must be charged or filled), and the availability of makes/models. The project further evaluates the robustness of its findings through sensitivity analyses for various parameters such as fuel prices, payback period, and technology progress over time.

This project recognizes that significant previous and ongoing efforts have been invested in providing DOE with insight into costs, emissions, and energy consumption of different transportation technologies, and accordingly, the project leverages existing analyses where available, including Autonomie modeling of vehicles, EV-FAST modeling of electricity prices, information from the U.S. Energy Information Administration (EIA) for fuel costs, and GREET® modeling for environmental metrics.

Results

This analysis explores how multiple factors (e.g., fuel and technology costs, financials, and vehicle usage) affect the "optimal" technology for various on-road transportation segments, highlighting the value of multiple solutions to achieve cost-competitiveness in different segments under a variety of assumptions. LCOD is used as one metric to compare alternative powertrains across transportation market segments, to find the least-cost technology within a given market segment. LCOD is defined as the sum of the cost of purchasing a vehicle, amortized over its lifetime driving, and the operational costs of the vehicle, including per-mile fuel cost and other costs, such as maintenance, insurance, and registration.

Figure I.13.1 illustrates the cost-optimal powertrain for different transportation segments in 2035. The color-coded cells represent the lowest-cost technology vehicle–fuel combination, for each segment, given a set of vehicle, fuel, and economic assumptions. The horizontal axis represents changes in vehicle classes, ranging in size from a compact car to a pickup truck. The vertical axis represents the change in driving, and implicitly the change in fuel costs. This axis also represents different assumptions for electricity prices. While each of the other fuels in our analysis is assumed to have a singular price, electricity is unique in its potential variation of price driven by consumer choice of charging location and timing. Average electricity prices reflect Annual Energy Outlook (AEO) residential rates (assuming 100% home charging, no charging equipment cost, and no time-of-use rates). To represent a wide range of potential electricity prices, low price is half the cost of residential rates, as a result of access to cheaper electricity, while high price is assumed to be twice the cost of the AEO residential case, as a result of faster charging (e.g., cost of public fast charging stations that might be more expensive than residential charging, especially if station utilization is low [Muratori et al. 2019]). Additionally, it is assumed that all fuels are fully available in each market, i.e., re-fueling infrastructure is fully built out. Figure I.13.1 also shows similar results for medium- and heavy-duty vehicles. The horizontal axis represents different vehicle classes, while the vertical axis represents different VMT numbers representative of variations in real-world driving in these size classes.

Lowest LCOD powertrain (LDV) **2035**

Annual driving	Electricity price	Compact	Midsize	Small SUV	Mid SUV	Pickup
8,000 mi	Low Price	BEV	BEV	BEV	BEV	BEV
	Avg. Residential	BEV	BEV	BEV	BEV	BEV
	High Price	CNG ICE	CNG ICE	CNG ICE	CNG ICE	CNG ICE
11,000 mi	Low Price	BEV	BEV	PHEV	PHEV	PHEV
	Avg. Residential	H2 FCEV	H2 FCEV	H2 FCEV	H2 FCEV	CNG ICE
	High Price	H2 FCEV	H2 FCEV	H2 FCEV	H2 FCEV	CNG ICE
14,000 mi	Low Price	H2 FCEV	PHEV	PHEV	PHEV	PHEV
	Avg. Residential	H2 FCEV	H2 FCEV	H2 FCEV	PHEV	PHEV
	High Price	H2 FCEV	H2 FCEV	H2 FCEV	H2 FCEV	H2 FCEV
18,000 mi	Low Price	PHEV	PHEV	PHEV	PHEV	PHEV
	Avg. Residential	H2 FCEV	PHEV	PHEV	PHEV	PHEV
	High Price	H2 FCEV	H2 FCEV	H2 FCEV	H2 FCEV	HEV

Lowest LCOD powertrain (MDV & HDV) **2035**

Annual driving	Class 2b-5	Class 6-7	Class 7	Class 8
25th percentile distance	FCEV	FCEV	BEV	CNG
50th percentile distance	FCEV	FCEV	BEV	CNG
75th percentile distance	BEV	BEV	BEV	CNG
90th percentile distance	BEV	BEV	BEV	CNG

Legend:

BEV	Battery electric vehicle
Biofuel ICE	Biofuel internal combustion engine vehicle
CNG ICE	Compressed natural gas vehicle
Diesel ICE	Diesel internal combustion engine vehicle
Gasoline ICE	Gasoline internal combustion engine vehicle
H2 FCEV	Hydrogen fuel cell electric vehicle
HEV	Hybrid electric vehicle
PHEV	Plug-in hybrid electric vehicle

Figure I.13.1 Lowest LCOD technologies for different market segments for light-duty and medium- to heavy-duty vehicles in 2035 for AEO reference case fuel prices and successful achievement of EERE program office technology targets

Results highlight some key trends. First, this graphic presents many different powertrains, which is indicative of the fact that the high technology case in the Autonomie modeling represents a scenario in which many technologies approach or reach cost parity with conventional internal combustion engine vehicles. This case was selected because alternative powertrains are only cost-competitive with incumbent fuels when optimistic technological progress is assumed. Plug-in vehicle powertrains are most cost-competitive when electricity prices are low; at high electricity prices, no plug-in vehicle is most economical in its segment. Light-duty FCEVs are the lowest-cost solution for other segments, especially for higher VMT segments, thanks to quick assumed reduction in technology costs. CNG vehicles are cost-competitive for some short-range light-duty vehicles and in the heavy-duty vehicle segments owing to extremely low fuel cost projections in AEO 2019, but these results are predicated on reductions in costs for natural gas fuel tanks and availability of fueling infrastructure. Likewise, the low per-mile cost of electricity allows BEVs to make a foothold in medium-duty cases at high driving distances, again assuming that the vehicle has sufficient capabilities to be used within the segments and that there is enough charging infrastructure. Modeling also shows BEVs to be the most cost-effective vehicles in Class 7 because of the comparably short driving range representative of typical day-cab duty cycles. FCEVs represent the lowest-cost solution for smaller trucks with relatively low annual mileage, again thanks to quick assumed reduction in technology costs.

As the LCOD depends mainly upon fuel costs and initial capital costs, the research team performed a sensitivity analysis to evaluate the robustness of the project model under two different scenarios: (1) fuel prices and (2) vehicle lifetime (ownership period). Results show that oil prices can significantly alter the "best" solution across segments. Given the high volatility of oil prices and the high uncertainty in future projections, identifying a robust alternative fuel for different medium- and heavy-duty applications remains a challenge. Similarly, results show that different assumptions for vehicle lifetime (or ownership period) determine the ability of high-efficient alternative fuel vehicles to recover the higher vehicle cost through fuel savings as more or fewer miles are driven.

Conclusions

The results reported here highlight the importance of considering different "segments" when comparing alternative vehicle–fuel options. The transportation sector is heterogeneous and can be seen as divided into different "market segments." These market segments are characterized by different vehicle sizing and performance requirements to serve different purposes or applications, different use cases, and different annual VMT. The project compares the LCOD of different vehicle–fuel combinations across different segments, determining that there appears to be no "silver bullet" for all applications. Moreover, results are shown to be sensitive to major assumptions (e.g., fuel prices, vehicle lifetime, and technology cost progress over time) that are affected by significant uncertainty.

While this analysis focuses on LCOD, which provides useful insights on technology competitiveness, it is important to understand that consumers and fleet operators' decisions do not always depend solely on cost; several other factors play a key role in determining technology adoption. Among these, driving experience and consumer preference for different alternatives, convenience of fueling (e.g., the locations where vehicles can be charged or filled, the time that it takes to charge or fill, and the frequency at which a vehicle must be charged or filled), fleet requirements for low-emissions transportation solutions, and the availability/familiarity of makes/models. The insights from this analysis show that research and development across all technologies is needed to guarantee technology development toward an affordable, sustainable, resilient, and secure energy future for the U.S. transportation sector.

Key Publications

1. Gohlke, D., R. Desai, and M. Muratori. "Least-Cost Technologies For Different Transportation Segments: A Sensitivity Analysis." To be presented at Transportation Research Board Annual Meeting, Washington, DC, January 2020.

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I.14 Transportation Data Book and Fact of the Week

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Start Date: October 1, 2019 End Date: September 30, 2022
Project Funding (FY19): $400,000/year DOE Share: $400,000/year Non-DOE Share: $0

Project Introduction

To inform stakeholders, transportation analysts and Vehicle Technologies Office (VTO) staff require quality current and historical data and information on the transportation sector. The Transportation Data Program (TDP) provides a wealth of information that is used as a U.S. Department of Energy (DOE) resource to improve analyses of the transportation sector; these studies contribute to program planning, evaluation, and technology research in the public and private sectors. Stakeholders use these data to help move the United States toward affordable transportation, reduce petroleum dependence, and increase national security.

Objectives

The objective of the TDP is to provide quality data and information for the VTO Analysis Program and stakeholders. Specifically, the project has (1) produced the text, graphics, and data for a Fact of the Week (FOTW) that is posted on the VTO website each week and is sent to a subscription list via email, (2) produced updated tabular and graphical data on the transportation sector that were posted on the Transportation Energy Data Book website twice a year as Editions 37.1 and 37.2, and (3) produced a draft of Edition 38 of the Transportation Energy Data Book, including updated data and information.

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.14.1). Data are discovered from a myriad of public and private sources, and ORNL performs 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 and the National Energy Renewable Laboratory), government agencies (e.g., the 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 Microsoft (MS) Word and/or MS Excel. DOE reviews and approves each FOTW and the tabulations/graphics in the Transportation Energy Data Book before final publication. The FOTW is published on the VTO Transportation Fact of the Week webpage (https://energy.gov/eere/vehicles/transportation-fact-week), and an email with the FOTW is sent (via the GovDelivery system) to the subscription list every week, typically on Monday afternoons. The PDF and MS Excel files for the Transportation Energy Data Book (https://cta.ornl.gov/data/index.shtml) are posted on the website hosted by ORNL. The major topics for the TDP publications are provided in Table I.14.1.

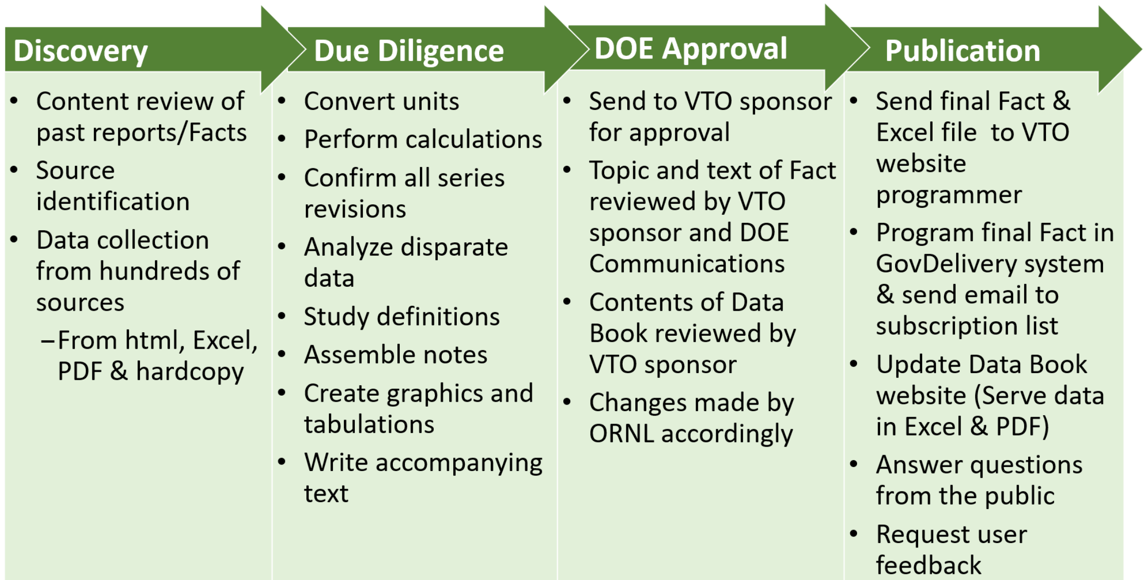

Figure I.14.1 Approach for the transportation data program at ORNL

Table I.14.1 Major Topics for the Transportation Data Program at Oak Ridge National Laboratory

Transportation Energy Data Book Topics	Fact of the Week Topics
Petroleum	Sales
Energy	Petroleum
Light Vehicles & Characteristics	Fuel Economy
Heavy Vehicles & Characteristics	Travel Behavior
Alternative Fuel & Advanced Technology Vehicles & Characteristics	Gasoline
Transit & Other Shared Mobility	Electric Vehicles
Fleet Vehicles & Characteristics	Cost to Consumer
Household Vehicles & Characteristics	Diesel
Nonhighway Modes	Import/Export
Transportation & the Economy	Infrastructure
Emissions	Heavy-duty Vehicles
Energy Conversions	Behavior/Ownership, and More…

Results

FOTW 1049 through 1101 were posted on the VTO website during fiscal year (FY) 2019 (Table I.14.2). For FY 2019, FOTW content accounted for 220,256 pageviews, or 35% of all VTO website pageviews during the fiscal year—a 5% increase over FY 2018. Of those pageviews, 203,028 were unique visits, meaning that some visitors (17,231) to FOTW content were repeat visitors. Of all VTO website visits, 47% (195,145) 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—119,600, or 29% of all website pageviews during the fiscal year.

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. As of the end of FY 2019, there were 26,574 subscribers to the Transportation FOTW newsletter.

Table I.14.2 Facts of the Week Posted on the VTO website in FY 2019

Fact Number	Fact Title	Date Posted on Website
1101	Medium/Heavy Trucks Were 4% of the Vehicle Population but Accounted for 26% of Fuel Use in 2017	September 30, 2019
1100	The United States Had Nearly 20% of World Automotive Lithium-ion Battery Manufacturing Capacity in 2016	September 23, 2019
1099	Australia, Chile, and Argentina produced 91% of the World's Lithium	September 16, 2019
1098	More Than Half of Transit Buses in the U.S. Were Powered by Alternative Fuels and Advanced Technologies in 2018	September 9, 2019
1097	Manufacturing Accounted for 40% of Employment in the Motor Vehicles and Component Parts Sector in 2018	September 3, 2019
1096	Employment Grew by 3% for the Motor Vehicles and Component Parts Sector from 2017 to 2018	August 26, 2019
1095	The Average Age of Light-Duty Vehicles Has Increased to 11.8 Years	August 19, 2019
1094	The Transportation Sector Consumes More Petroleum than All Other Sectors Combined	August 12, 2019
1093	For Model Year 2018, Electric-Drive Vehicle Models Were Available in Nine Different Size Classes	August 5, 2019
1092	More Than Half of All Children Typically Travel to School via Private Vehicle	July 29, 2019
1091	The Rise in Prices for Used Vehicles Outpaced That of New Vehicles	July 22, 2019
1090	Used Vehicle Sales Are More Than Double the Number of New Vehicle Sales	July 15, 2019
1089	There are More Than 68,800 Electric Vehicle Charging Units in the United States	July 8, 2019
1088	Transit Rail Ridership Was 64% Higher in 2018 than in 1990	July 1, 2019
1087	Non-Hybrid Stop/Start Systems Were Installed on 35.7% of All Light-Duty Trucks Produced in Model Year 2018	June 24, 2019
1086	Seventy-five Percent of Plug-in Vehicles Sold in the United States in 2018 Were Made in the United States	June 17, 2019
1085	The Average Annual Gasoline Price in 2018 Was $2.74	June 10, 2019
1084	Since 2013 U.S. Crude Oil Imports Have Been Less Than 10.2 Million Barrels Per Day	June 3, 2019
1083	Growth in Vehicle-miles of Travel and Number of Vehicles Outpaces Population Growth	May 27, 2019
1082	In 2018, 27% of New Light-Duty Vehicles Had Fuel Economies Over 30 Miles per Gallon	May 20, 2019
1081	Plug-in Vehicles in the United States Displaced 323 Million Gallons of Gasoline in 2018	May 13, 2019
1080	U.S. Plug-in Vehicles Consumed Nearly Three Terawatt-hours of Electricity in 2018	May 6, 2019
1079	More Than 1 Million Plug-in Vehicles Were Sold in China in 2018	April 29, 2019
1078	Model Year 2018 Vehicles Have Record High Fuel Economy with Improved Horsepower and Acceleration	April 22, 2019
1077	Of Emerging Fuel Saving Technologies, Gasoline Direct Injection Was the Most Widely Adopted in 2018	April 15, 2019
1076	Most New Light-Duty Vehicles Have Transmissions with at Least Six Speeds	April 8, 2019
1075	Most Common Maximum Speed Limit for Trucks in 2017 Was 70 Miles per Hour	April 1, 2019

1074	Gasoline Taxes in the United States Are a Small Share of Gasoline Cost Compared to Other Countries	March 25, 2019
1073	Crude Oil Cost Accounted for 50% of Gasoline Price in 2017	March 18, 2019
1072	Light-Duty Vehicles Accounted for the Majority of Transportation Energy Consumption	March 11, 2019
1071	Improvements in Fuel Economy for Low-MPG Vehicles Yield the Greatest Savings	March 4, 2109
1070	Forty-One Models of Light-Duty Plug-In Electric Vehicles Were Available in Model Year 2018	February 25, 2019
1069	Most Valuable Commodities Shipped: Motor Vehicles and Parts were Second Only to Mixed Freight in 2017	February 18, 2019
1068	The 2017 Commodity Flow Survey Shows Freight Movement in the United States of 12.5 Billion Tons Valued at $14.4 Trillion	February 11, 2019
1067	Annual Light-Duty Vehicle Sales for 2018 Totaled 17.2 Million	February 4, 2019
1066	The Travel Density of Urban Interstates was 2.5 Times Higher than Rural Interstates in 2016	January 28, 2019
1065	Only 26% of 16-year-olds were Licensed Drivers in 2016	January 21, 2019
1064	Median All-Electric Vehicle Range Grew from 73 Miles in Model Year 2011 to 125 Miles in Model Year 2018	January 14, 2018
1063	The United States Exported 1.68 Trillion Cubic Feet of Natural Gas to Mexico in 2017	January 7, 2019
1062	U.S. Exports of Natural Gas Surpass Imports in 2017	December 31, 2018
1061	Vermont Had a Growth Rate of 56.4% for Plug-in Vehicle Registrations per Capita from 2016 to 2017	December 24, 2018
1060	Transportation Services Index Shows Freight at an All-Time High in August 2018	December 17, 2018
1059	California Had the Most Plug-in Vehicle Registrations per 1,000 People in 2017	December 10, 2018
1058	Two-thirds of all Housing Units Had a Garage or Carport in 2017	December 3, 2018
1057	One Million Plug-in Vehicles Have Been Sold in the United States	November 26, 2018
1056	Petroleum Net Imports as a Share of U.S. Consumption in 2017 was at the Lowest Level Since 1967	November 19, 2018
1055	Michigan Continues to Lead in Light-Duty Vehicle Production	November 12, 2018
1054	The Transportation Sector Used 43.4 Billion Cubic Feet of Natural Gas for Vehicle Fuel in 2017	November 5, 2018
1053	Sales of Crossover Vehicles Are Up 116.9% in the Last Ten Years	October 29, 2018
1052	Four Networks Maintain Over 60% of 22,343 Level 2 and DC Fast Charging Stations	October 22, 2018
1051	All-Electric Vehicles Make Up 53% of Plug-In Vehicle Sales to Date	October 15, 2018
1050	Vehicles per Thousand People in China in 2016 was Similar to the United States in 1923	October 8, 2018
1049	The United States Consumed 20% of World Petroleum in 2017	October 1, 2018

The first online-only edition of the Transportation Energy Data Book was published in 2017. Having no printed copy allows for mid-year updates to the tables and graphics posted online. In April 2019, Edition 37.1 debuted online with 65 tables and 9 figures updated with more recent data than was published in the original Edition 37. In August 2019, another 43 tables and 13 figures were updated for Edition 37.2. The draft of Edition 38 was completed and delivered on September 30, 2019, with a total of 226 tables and 70 figures of transportation data, many with historical series going back to 1970. The three appendices contain an additional

51 tables. New for Edition 38 are a chapter called Transit and Other Shared Mobility and an appendix with energy tables and figures that consider electricity generation and distribution. Edition 38 will be posted to the website once DOE has reviewed and approved the content.

The Transportation Energy Data Book website (Figure I.14.2) was completely redesigned in 2019 and assigned a new web address: https://tedb.ornl.gov. The former web address redirects users to the new address. The site was designed with a keyword search feature to help users find the data they need quickly and efficiently in both PDF and MS Excel. In addition to enabling data access, the new homepage has five rotating data highlights, links to the Transportation FOTW and Argonne National Laboratory's E-Drive Monthly Sales, and a feedback form so that users can easily contact the project principal investigator, Stacy Davis. The five highlights are changed three times each year when the website is updated. Other pages on the website provide access to an archive of older reports, citation information, and project contact information.

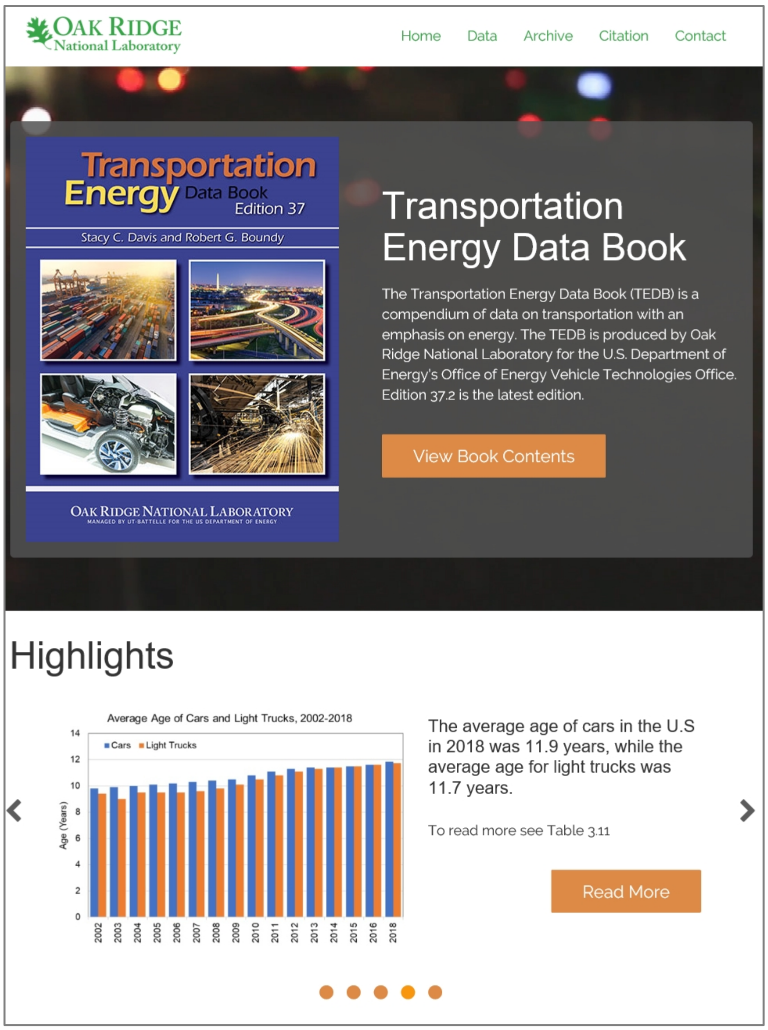

Figure I.14.2 Transportation Energy Data Book website home page

The Transportation Energy Data Book website had 93,495 pageviews in FY 2019, including 7,853 PDF file downloads and 10,115 MS Excel file downloads. Google Scholar reports 3,220 citations for the Transportation Energy Data Book. Website traffic logs show that 55.3% of the Transportation Energy Data Book website traffic is coming directly to the website and another 32.7% from search engines, with the remainder from external referrers (11.9%) and social media (0.1%).

Data collected in the TDP have also provided input to other VTO programs and other agency models, such as MA^3T, GREET®, ADOPT, ParaChoice, prospective program benefits analysis, the U.S. Energy Information Administration's National Energy Modeling System, and the U.S. Environmental Protection Agency's Motor Vehicle Emission Simulator (MOVES) model.

Conclusions

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

Key Publications

1. Davis, S. and R. Boundy (2019). "Transportation Energy Data Book: Edition 38." ORNL/TM-2019/1333, Oak Ridge National Laboratory, Oak Ridge, Tennessee. [Draft completed in FY 2019. To be published in final form in FY 2020.]

I.15 Charging Behavior and Grid Impact of Electrified Class 8 Semi-Trucks

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Project Funding (FY19): $200,000 DOE Share: $200,000 Non-DOE Share: $0

Project Introduction

Passenger electric vehicle (EV) cumulative sales passed the 4 million mark in 2018 (1 million EVs have been sold in the United States alone) and continue to grow rapidly in many countries—with EV stock increasing by over 60% from 2017 to 2018. As transportation electrification progresses and economies of scale emerge, it is important to consider the opportunity for heavy-duty vehicle electrification in the freight trucking industry.

Trucks account for ~20% of all energy consumed by the U.S. transportation sector, and fuel accounts for a major portion of operating costs for freight companies (EIA 2019; FHWA 2017). The variety and complexity of operations, however, make it challenging to assess the feasibility of heavy-duty fleet electrification and its associated impact on energy use. While some studies focus on exploring networks of extreme fast chargers to support truck electrification (e.g., multi-megawatt charging capabilities at truck stops), current daily operations of many medium- and heavy-duty trucks align well with opportunities to recharge at depots when vehicles are parked, usually overnight, as shown in Figure I.15.1.

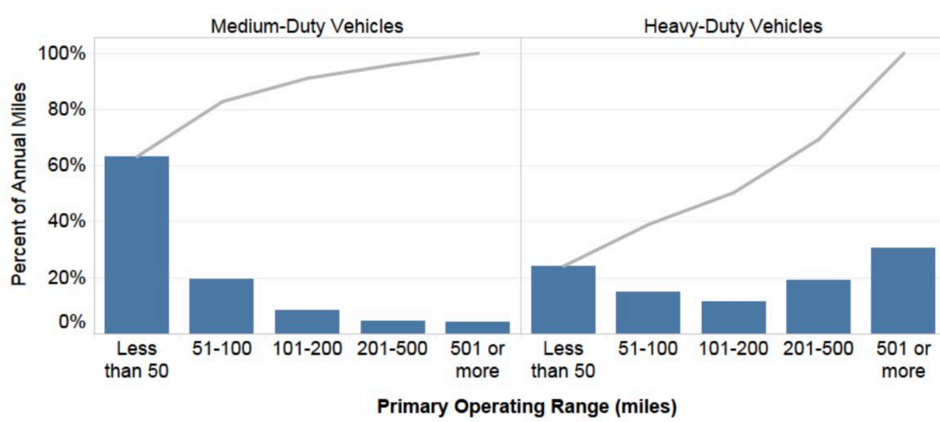

Figure I.15.1 Percentage of total annual miles (bars) and cumulative percentage of total (line) by primary operating range for medium-duty vehicles (left) and heavy-duty vehicles (right). From Mai et al. 2018.

This project focuses on depot charging of Class 8 semi-trucks, which is likely to be the first charging solution for these applications. In this context, the impact of truck electrification on electricity systems, particularly the distribution network (substations, feeders, transformers, etc.), remains unexplored. Important questions include the following:

- What is the potential for heavy-duty fleet electrification based on existing operations, and what vehicle range is required?
- What are the charging infrastructure requirements and charging strategies for electric freight fleet operators? Can trucks be charged at their base depot during dwell times dictated by other logistics rather than imposed by charging requirements?
- What are the grid impacts for a variety of operations, fleets (vehicle characteristics and number of vehicles), charging infrastructure, and recharge strategies?

Tesla, the leading manufacturer of light-duty EVs, has announced plans to bring an electric Class 8 semi-truck to market in the near future. For this project, Tesla will collaborate with the National Renewable Energy Laboratory (NREL) to better understand the opportunities and impacts depot-based charging of heavy-duty vehicles on the U.S. power system through analysis of real-world fleet operational data and electricity distribution systems.

Objectives

The objective of this project is two-fold:

- Develop a set of electricity load profiles using real-world operating data for electric Class 8 semi-trucks. Profiles will incorporate expected variations in duty cycles, battery size, charging infrastructure, and recharge strategies.
- Evaluate the impacts of these load profiles on the electrical distribution infrastructure, and develop a taxonomy of distribution grid upgrades (type, cost, and timing) needed to accommodate different electric semi-truck adoption and charging scenarios.

This cross-industry collaboration will leverage NREL's expertise in analysis and modeling, Tesla's experience designing and working with heavy-duty electric trucks and associated operational data, and Southern Company's and Oncor's experience and associated data on electrical distribution systems and knowledge of the cost and scope of upgrades required to accommodate truck electrification.

Approach

This analysis will leverage real-world duty cycles for Class 7/8 tractors operating in the United States to derive operating constraints (e.g., operating time and vehicle miles traveled [VMT]) and charging potential (e.g., dwell times and durations) for electric Class 8 trucks. Relevant operating characteristics, combined with vehicle characteristics (battery size, power acceptance, charge tapering, powertrain efficiency), available charging infrastructure, and recharge strategies will be used to establish a set of electric semi-truck charging load profiles under a variety of scenarios. To assess the impact of electric semi-truck charging on electrical distribution networks, individual load profiles will be aggregated to approximate large-scale electrification scenarios (e.g., 10, 20, 50+ vehicles connected to an appropriate distribution feeder). A taxonomy of grid upgrades (category, cost, timing) will be developed with guidance from Southern Company and Oncor, enabling assessment of cost- and timing-related impacts associated with accommodating various levels of semi-truck electrification on the electrical grid.

Results

Initial results have been generated through leveraging NREL's commercial fleet vehicle database, FleetDNA,[10] to obtain real-world duty cycles from more than 3,000 days of driving for Class 7/8 tractors operating in the United States as part of 14 different fleets from nine companies. These data include operations for a wide range

[10] NREL's Fleet DNA clearinghouse of commercial fleet vehicle operating data helps vehicle manufacturers and developers optimize vehicle designs and helps fleet managers choose advanced technologies for their fleets. https://www.nrel.gov/transportation/fleettest-fleet-dna.html

of vocations, such as beverage delivery, food delivery, and other local, regional, and long-haul activities. Relevant characteristics describing operating constraints (e.g., operating time and VMT) and charging potential (e.g., dwell times and durations) can be derived across multiple vocations using this dataset (see Figure I.15.2).

provider	vocation	weight class	location	vehs	veh. days	oper. days	VMT/ oper. day	% oper. days < 300 mi.	total dwell-hrs / oper. day	base dwell-hrs / oper. day	max base dwell period / day
Anheuser Busch	Beverage Delivery	7	Denver, CO	9	51	31	38.3	100.0	22.5	13.7	7.3 hrs
Coke	Beverage Delivery	8	Fresno, CA	12	320	185	102.9	100.0	21.3	14.8	8.2 hrs
			Miami, FL	9	70	43	88.6	95.3	20.3	7.8	4.5 hrs
			San Diego, CA	12	325	181	55.7	100.0	21.9	14.3	8.7 hrs
Costco	Warehouse Delivery	7	Los Angeles, CA	10	178	111	82.6	100.0	21.4	5.9	4.3 hrs
FedEx	Parcel Delivery	7	Ontario, Canada	11	192	102	30.5	100.0	22.8	18.5	12.0 hrs
Pepsi	Beverage Delivery	8	Los Angeles, CA	10	218	135	41.4	100.0	22.1	14.8	7.6 hrs
			San Francisco, CA	12	260	149	89.2	98.6	21.1	15.1	7.8 hrs
Shamrock	Food Delivery	8	Denver, CO	22	579	345	143.0	85.2	20.3	8.7	4.6 hrs
UPS	Parcel Delivery	8	Houston, TX	6	92	81	484.9	28.4	15.1	5.9	3.5 hrs
Veritable Vegetable	Food Delivery	7	San Francisco, CA	9	191	132	171.6	76.5	19.5	10.6	6.0 hrs
Walmart	Line Haul	8	Grove City, OH	23	311						
			Loveland, CO	8	116				TBD		
			Sanger, TX	8	135						
TOTAL			(11 locations)	161	> 3,038	> 1,495					

Figure I.15.2 Summary of heavy-duty fleet considered.

The results summarized in Figure I.15.2. highlight significant variability across applications/companies, but consistently show that many fleets operate vehicles for less than 300 miles for the vast majority (or virtually all) days, potentially enabling an electric truck with 300 miles of range to replace existing diesel vehicles (see % of operating days <300 miles column). Moreover, results show that many fleets have vehicles dwelling at their home base for 6 hours or more during each operating day, enabling depot charging opportunities. These results will be analyzed further to identify ranges of time during which vehicles dwell at their base to build possible charging load profiles.

Conclusions

Early results confirm that, for some Class 8 semi-truck applications, current daily operations (in terms of miles driven, operating hours and dwell at base depot) align well with opportunities to recharge electric trucks with 300 miles of range at depots when vehicles are parked. Vehicle usage (in terms of miles driven, and time-resolved dwell at base depot) will be translated into prospective scenarios of charging profiles, and the team will assess the impacts and requirements imposed by those profiles from an electricity distribution perspective throughout the course of the project.

Key Publications

1. N/A (draft paper expected in Summer 2020)

References

1. EIA (U.S. Energy Information Administration) (2019). "Monthly Energy Review." DOE/EIA-0035(2019/2). January 2019.
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I.16 Lifetime Driving Schedules of Fuel-Efficient Vehicles

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Start Date: July 2019 End Date: June 2020
Project Funding (FY19): $130,000 DOE Share: $130,000 Non-DOE Share: $0

Project Introduction

A vehicle mileage schedule estimates the annual miles driven by a typical vehicle each year as the vehicle ages. These schedules are relevant for calculating the total mileage that vehicles are driven in their lifetimes and are therefore used in calculations of levelized cost of driving (LCOD) and cradle-to-grave environmental lifecycle assessments. However, there is a high degree of uncertainty in the vehicle mileage schedules that are typically used for these calculations. These travel schedules are low-fidelity, grouping together vehicles with disparate fuel economy ratings and typically disaggregating only to a broad vehicle type level (e.g., cars vs. light trucks). Present analysis may not capture differences in how vehicles are operated—differences beyond the vehicle size—particularly for variables such as fuel economy.

This project uses travel behavior from the National Household Travel Survey (NHTS) and data from annual odometer readings in Texas and Massachusetts to generate new vehicle mileage schedules for light-duty passenger vehicles. In particular, these updated vehicle mileage schedules will be partitioned based on fuel economy to determine whether vehicles with better fuel economy are driven more intensively. Highly efficient vehicles have lower fuel costs (per mile), which may incentivize more intensive driving. If a correlation between fuel economy and driving distance is established, it would further lower the per-mile cost of efficient vehicles, as the purchase price of these vehicles would be amortized over a greater number of miles.

Objectives

This project is generating vehicle mileage schedules for light-duty vehicles in the United States, as a function of vehicle vintage, size, and fuel economy. The schedules can be used to supplement similar information published by the U.S. Department of Transportation (DOT) and the U.S. Environmental Protection Agency (EPA). This information could also be used by other researchers to inform estimates of the rebound effect for vehicle miles traveled (VMT) due to improved fuel economy.

Using these new vehicle mileage schedules, the project estimates LCOD for various light-duty vehicles, including different vehicle types, fuel economies, and powertrains. This LCOD will be compared and contrasted with previously published mileage schedules to establish the degree of sensitivity for economic calculations. Findings will be published for use by the broader research community.

Approach

This project contains three phases, described below: synthesis and analysis of data, LCOD comparison, and publication of results.

Task 1: Synthesis and analysis of data. Recorded odometer data and estimated annual travel from survey results are used to generate new light-duty vehicle mileage schedules. Lawrence Berkeley National Laboratory has compiled a multi-year dataset of annual odometer readings from the emissions inspection program (in 17 counties) and the safety inspection program (in the remaining counties) of Texas; the data were previously used to estimate the effect of changes in gas prices on annual VMT (Wenzel et al. 2018). A similar, though smaller, dataset is available for the state of Massachusetts, which can be used to test the geographical robustness of the analysis (Metropolitan Area Planning Council 2018). Argonne and Oak Ridge National Laboratory have been exploring vehicle data from the most recent NHTS (DOT FHA 2019). The project team checks for any systematic differences between the three datasets. The data are rigorously analyzed to estimate mileage schedules for cars and light trucks, to compare directly with previously published mileage schedules. Fuel economy will be treated as an independent variable for estimating annual driving intensity. This will initially be done by binning vehicles based on their fuel economy, but if possible, the team will derive a closed-form analytic expression for annual driving distance as a function of both age and fuel economy, i.e., VMT (age, mpg).

Task 2: Levelized cost of driving comparison. Using the new mileage schedules derived in Task 1, the project will calculate LCOD for vehicles with different fuel economies, corresponding to vehicles available today and those modeled for other Vehicle Technologies Office analysis projects. LCOD will also be calculated for the same vehicles using previously published mileage schedules (e.g., Berkowitz 1995, DOT 2018, EPA 2016, and Lu 2006). Assumptions such as the discount rate and vehicle lifetime will be varied to determine the magnitude of the potential impact on LCOD when using the updated mileage schedules from Task 1.

Task 3: Publication of results. So that other researchers can use this analysis, updated mileage schedules from Task 1 and LCOD comparisons from Task 2 will be published in fiscal year (FY) 2020.

Results

Preliminary results for VMT mileage schedules have been generated. Figure I.16.1 shows representative data for vehicle mileage schedules, for data derived from Texas odometer readings (left) and the NHTS (right). The vertical axis of each of these graphs is the VMT per year, while the horizontal axis represents the vehicle’s age. Each of these curves shows a gradual decrease in annual VMT as a function of vehicle age. The Texas data are for passenger cars for six separate years, showing that the general trend is reproducible year-over-year. The NHTS data show mileage schedules for four different vehicle types (cars, sport utility vehicles, vans, and pickup trucks). Results show that mileage schedules have a similar general trend for each of these light-duty vehicle types.

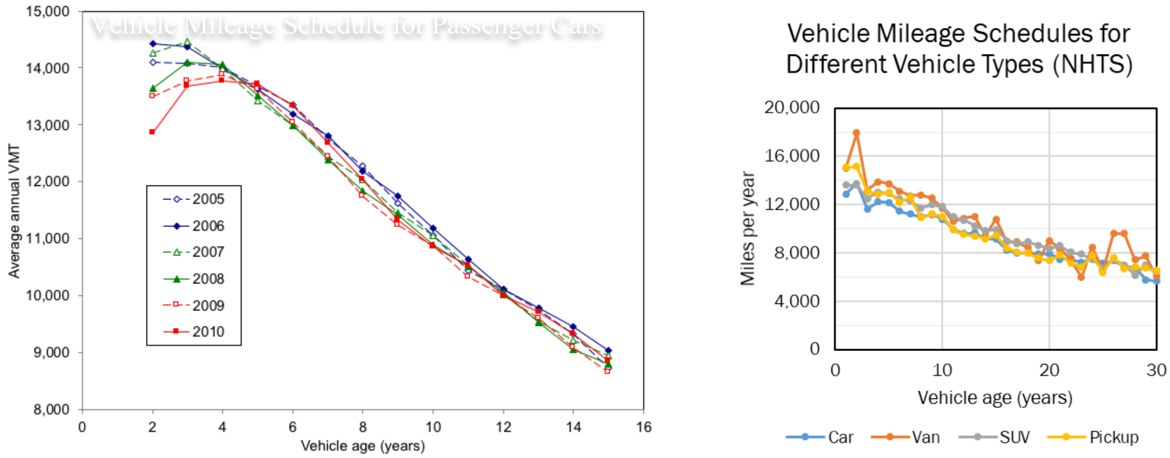

Figure I.16.1 Preliminary vehicle mileage schedules derived from Texas odometer data (left) and the NHTS (right)

In FY 2019, data were acquired for fuel economy for the vehicles in each dataset to enable addition of a new dimension to the results.

Conclusions

Progress is being made on data needed for analysis to generate vehicle mileage schedules as a function of vehicle age and fuel economy. Preliminary results generating mileage schedules show a smooth reduction in miles traveled as vehicles age. These results will be expanded to include fuel economy data in FY 2020. The final mileage schedules will be used in LCOD analyses to find costs that are more representative of real-world driving patterns, and results will be published for other researchers to use.

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I.17 Medium-/Heavy-Duty Vehicle Choice Modeling in ADOPT

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Start Date: June 2019 End Date: June 2020
Project Funding (FY19): $150,000 DOE Share: $150,000 Non-DOE Share: $0

Project Introduction

The medium- and heavy-duty (MDHD) vehicle benefits analysis performed for the Vehicle Technologies Office (VTO) has historically assumed that alternative powertrains achieve the same performance as their conventional counterparts. The corresponding vehicle choice modeling has thus focused on the economics of up-front vehicle cost and future fuel expenditures as differentiators. However, performance is becoming more of a decision factor, as manufacturers develop alternative powertrains touted as having superior power, acceleration, and hill-climbing capability. Tesla's "Semi" battery electric semi-trailer truck and Toyota's "Project Portal" fuel cell electric drayage truck are examples of future alternative vehicles with enhanced performance. This project will enhance and apply the Automotive Deployment Options Projection Tool (ADOPT) model to assess the impact of performance differences on new technology adoption in the commercial vehicle market (and provide these results for use in the MDHD benefits analysis).

ADOPT estimates vehicle sales based on the most consumer-valued attributes, including price, fuel cost, acceleration, range, refuel time, and size, while considering the influence of existing regulations/incentives and other market conditions. To instill confidence in its results, ADOPT has been extensively validated by comparing the tool's sales estimates (given technology and market conditions in multiple past years and locations) to corresponding actual historic vehicle sales data, and ensuring that the results match in multiple different dimensions.

Objectives

The objective of this project is to complement the MDHD choice modeling currently used for VTO Benefits Analysis by including ADOPT's consideration of the tradeoffs among vehicle performance, vehicle range, and payload capacity (weight and volume), in addition to vehicle price and future fuel cost. The project provides VTO with an alternative perspective on MDHD technology adoption, enhancing the robustness of the benefits analysis. Additionally, the project enables benefits estimation from VTO research and development investments in both the light-duty (LD) and MDHD markets using a single integrated model (without the need for separate vehicle modeling and simulation). The project also adds an MDHD assessment capability to VTO's analysis portfolio, enabling research to address questions for which existing tools are not well suited.

Approach

ADOPT began as a LD vehicle choice modeling framework, but a separate recent project began to adapt ADOPT for application to MDHD analysis as well. This project builds on that past work and will more fully flesh out important input data for calibrating and applying the model to MDHD choice modeling (with an emphasis on modeling the most important vehicle sectors for supporting the MDHD benefits analysis). As Class 8 tractor-trailers account for most MDHD fuel consumption, the modeling efforts will focus initially on these vehicles. Subsequent scope expansions (pending U.S. Department of Energy [DOE] priorities and budget availability) may include (1) segmenting HD tractor modeling into Class 8 sleepers and Class 7/8 regional haul, (2) modeling Class 7/8 single-unit trucks, (3) modeling Class 4–6 trucks, and (4) modeling transit buses.

Results

A variety of changes to ADOPT were necessary to adapt the tool for modeling future HD vehicle sales and subsequent energy and emission impacts. One of the first changes involved updates to the category datasets. Category datasets define information relevant to the vehicle sales market, including vehicle life, driving patterns, fuel costs, and consumer characteristics. The following bullets detail category data types that have been updated for the Class 8 tractor-trailer modeling effort. The research team found while updating and testing the model that some categories, especially those that characterize consumers, do not directly translate from LD to HD vehicle choice modeling. While initial steps have been taken to account for these differences, future work will include further efforts to address these divergences.

ADOPT Category Data Updates:

- Maximum Penetration Rate: The maximum penetration rate is used to limit the rate at which a new vehicle powertrain could enter the market. Those limits may represent production ramp-up rate limits, expanding sales across the nation, or other limiting factors. For LD modeling, ADOPT estimates this limit based on the total sales volume for the best-selling non-conventional vehicle after its market introduction, such as the market penetration of the Toyota Prius as hybrid vehicles entered the LD market. For MDHD modeling, the maximum penetration rate was estimated based on sales of Class 8 compressed natural gas tractors.

- Vehicle Miles Traveled: The Vehicle Miles Traveled dataset was updated to reflect the number of miles driven per year for a Class 8 tractor over a lifetime of 20 years. The dataset was calculated using outputs from the Argonne National Laboratory VISION Model as well as the U.S. Census Vehicle Inventory and Use Survey (VIUS).

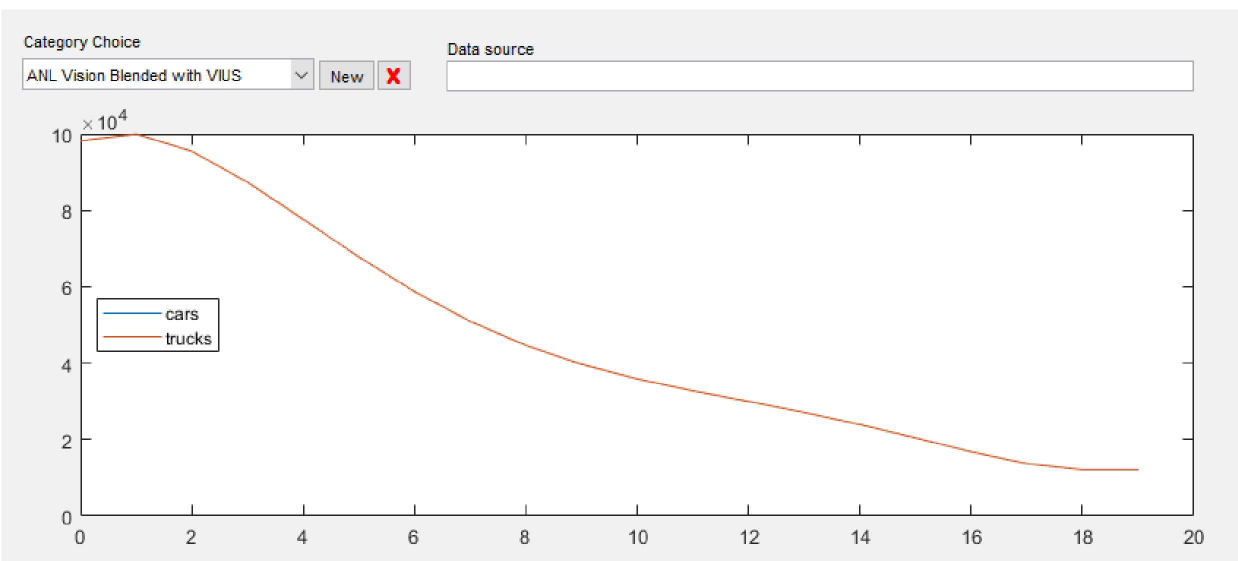

Figure I.17.1 VMT for a Class 8 tractor over a 20-year lifetime

- Vehicle Survival: The variable “Truck Median Age” within the survival category was updated to reflect the median age of Class 8 tractors. Data were taken from input files in the DOE Energy

Information Administration's (EIA's) National Energy Modeling System (NEMS) to support this update (showing Class 8 tractor survival dropping between the age of 25 years and 50 years).

- Household Income: For LD modeling with ADOPT, American households are broken up into six income bins, because income level has a large influence on price sensitivity in consumer purchases. However, household income is one of the variables that does not directly translate to the HD market. While household income is publicly available from the U.S. Census, it is much more difficult to obtain income-level information for all Class 8 commercial customers; and even if these data were available, the relationship between firm income and price sensitivity is unclear. The initial implementation strategy therefore changed the Household Income data category to a VMT category, based on the hypothesis that price sensitivity for commercial vehicle owners is based most strongly on the level of annual operating costs that they incur. Fuel costs (anticipated to dominate operating costs) can be directly calculated from VMT via the fuel price input already included in the model.

- Number of Households: For LD modeling with ADOPT, Number of Households represents the number of U.S. households that fall into each income bin. On account of the approach taken for HD ADOPT modeling to employ VMT bins instead of income bins, the analogous parameter to the Number of Households data category from LD ADOPT modeling is the number of truck drivers that fall within each VMT bin for the HD ADOPT modeling. Drivers who travel more miles on average will use more fuel, and thus the companies employing these drivers will have greater exposure to changes in fuel costs.

- Sales: Sales estimates through 2050 for HD vehicles have been updated based on historical information from EIA's NEMS as well as future projections from Deloitte.

Future Work

Most of the further work required to update ADOPT for MDHD modeling relates to identifying key decision factors for commercial consumers. These include seeking data and conducting subsequent research and analyses to confirm the extent to which higher truck VMT motivates buyers to seek lower fuel cost, and to assess the importance of performance specifications, such as truck acceleration capability, to the MDHD vehicle customer base. Based on the results of such analyses, requisite logic updates will be made within the MDHD ADOPT implementation via code changes and functionality testing. Updates will also be made to the tool's formatting and user interface to facilitate users' interpretation and application of the tool.

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I.18 Micro-Mobility Energy Bounding Analysis (National Renewable Energy Laboratory)

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Project Introduction

Micro-mobility options, including various forms of shared standard bicycles, electric scooters (e-scooters), and electric bicycles have rapidly emerged as transportation options in the urban landscape. To date, there is limited understanding as to the energy impacts of micro-mobility options. This project is using available data sources to develop a bounding analysis of the potential energy opportunities of micro-mobility. The research team will consider:

- Evaluation of the energy intensity of micro-mobility options
- Potential behavioral uptake to replace short, urban trips otherwise taken by more energy-intensive modes
- Impacts on the transportation system, including connection with public transit, and the capacity for micro-mobility to enable multimodal trips

Objectives

The objective of this project is to develop a bounding analysis of the energy opportunities of micro-mobility, including both favorable and unfavorable factors affecting potential energy outcomes. The bounding analysis will weigh existing travel needs with estimated behavioral adoption potential, cost, energy, and emission benefits of micro-mobility. The project team will then identify which components of micro-mobility are likely to matter most in possible near-future scenarios.

Approach

Micro-mobility options have been designed to serve travel needs for short trips, as well as first-/last-mile solutions for multimodal trips involving transit or other modes. The project aims to answer several key questions:

- What are the energy impacts of micro-mobility?
- Where might there be energy opportunities for micro-mobility?
- What outcomes from micro-mobility might be anticipated within the greater picture of the transportation system?

Answers to these questions will inform the development of the bounding analysis to identify the possible scale of micro-mobility's energy impacts, and the team can use the results to discern which facets may matter most.

As access to data specific to micro-mobility operations is limited, the project is being completed through analysis of existing datasets and factors, including:

- Current transportation behavior from the National Household Travel Survey (NHTS)
    - Portion of trips that may reasonably be satisfied via micro-mobility options
    - Portion of trips that may be converted to multimodal trips as enabled by micro-mobility
- Behavioral uptake factors
    - Literature review of relevant studies to inform assessment of the portion of the population that might reasonably be anticipated to use micro-mobility
    - Data insights from the WholeTraveler survey that may indicate uptake interest
- Energy estimation scenario development of micro-mobility use
    - Estimation of energy intensity of micro-mobility options as compared to the modes those options may replace
    - Development of various use-case scenarios of micro-mobility as informed by current travel needs, behavioral uptake factors, and energy intensity

In addition, the research explores different components of where demand/impacts could originate, identifies the areas with largest potential impacts, and delineates the most important data gaps necessary to further refine analyses. The project also endeavors to identify potential unintended and negative consequences that may result from micro-mobility, such as replacing physically active modes (e.g., walking) with more energy-intensive ones (e.g., e-scooters).

Results

The research team conducted a thorough review of relevant literature and identified available data sources. In general, micro-mobility operators do not make data regarding micro-mobility implementations publicly accessible other than in aggregate form; however, the team identified two operational micro-mobility datasets to inform the development of an energy bounding analysis for micro-mobility. The City of Austin, Texas, maintains a database of all dockless mobility trips (e-scooter and bicycle) taken since April of 2018. It is the largest dataset publicly available and is updated daily; as of September 16, 2019, the Austin database included records for more than 6.5 million e-scooter trips. The City of Louisville, Kentucky, also maintains a publicly available database of all e-scooter trips since August 2018 (300,000 records as of September 27, 2019).

Initially focusing on the Austin dataset, the team identified patterns of micro-mobility use. Figure I.18.1 shows that daytime is when most trips occur, on both weekdays and weekends. A more granular look into the data reveals that many trips occur between the hours of 10 AM and 3 PM, suggesting e-scooters are a key mobility option for short errands or lunch trips. The 85th percentile of distance for micro-mobility trips is 2,470 meters (1.53 miles). The 85th percentile of travel time for these trips is 17.1 minutes.

The research team next used NHTS data for Austin to gain insight into mode shares for trips that are shorter than 1.53 miles (the 85th percentile of trip distance in Austin E-scooter data). Among the 2.18 billion trips within the Austin NHTS data, Drive and Walk are the two major modes that travelers use currently for trips of 1.53 miles or less. Drive accounts for 61.8% of all trips, indicating substantial potential energy savings if these trips were made with e-scooters or other micro-mobility modes.

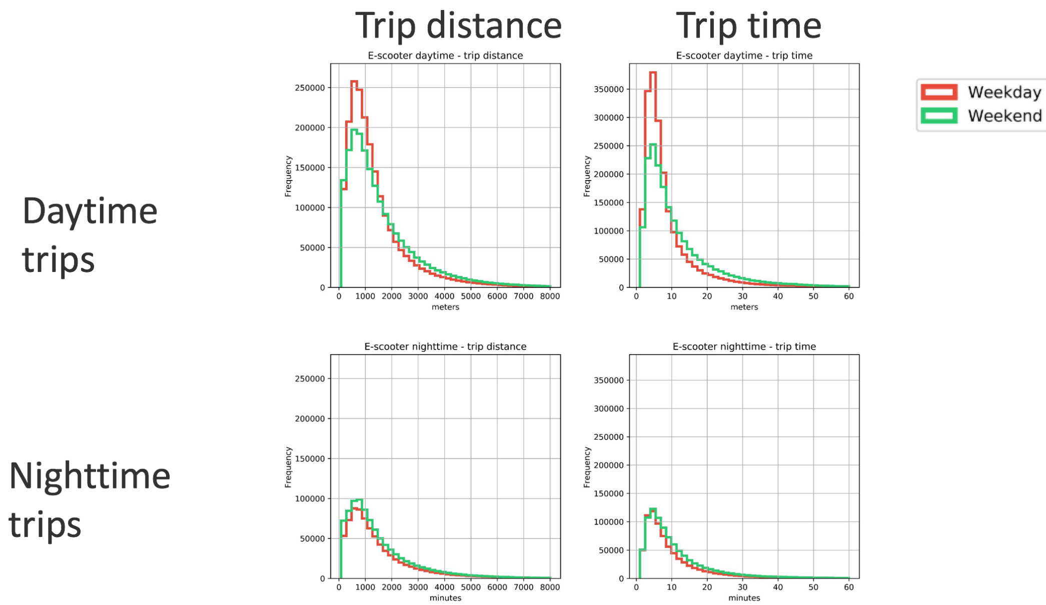

Figure I.18.1 Austin, Texas, micro-mobility trips by time of day
Source: National Renewable Energy Laboratory, using Austin data

Conclusions

The finding that the 85th percentile of micro-mobility trips is 1.53 miles suggests that these light vehicles are useful for mobility needs that are farther than the typical U.S. citizen is likely to want to walk, yet of a distance for which larger motor vehicles are not best suited. Further examination of the NHTS data reveals that the numbers of trips at distances of 0.1~0.4 miles and of 1 mile are relatively greater than those of other distance levels, even though more than 61% of those trips are currently conducted via car. These distances are well within the range of micro-mobility options.

Although this project is still active and analysis is in progress, micro-mobility appears to be a viable option to replace short car trips, but it is notable that some portion of micro-mobility use also replaces non-motorized modes, such as walking or biking. However, replacing larger motorized vehicles and longer-distance car trips through multimodal use of transit enabled by micro-mobility access appears to have promising potential. The project continues to explore the total energy impact and will publish its conclusions in the final report.

Key Publications

Publications in development.

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I.19 Vehicle MSRP Estimation Using Machine Learning Methods

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Project Introduction

For more than two decades, Argonne has supported the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) Analysis Program by estimating new technologies' impacts on energy consumption and cost over several thousand vehicles (Islam et al. 2018; Moawad et al. 2016). To estimate the overall impact, the Analysis group sponsors different vehicle market penetration tools that rely on Argonne's vehicle energy efficiency estimates as well as costs. Although vehicle energy models have been continuously developed and validated with test data, the uncertainty surrounding vehicle cost estimation has been increasing, with the latest studies being more than 10 years old.

Objectives

The goal of this project is to update current component and vehicle cost estimates and to estimate the increased efficiency per unit of cost ($/mpg) to increase the reliability of the overall VTO benefits.

Current methods rely on fixed equations to calculate each component cost and, ultimately, vehicle manufacturing cost. The vehicle manufacturer's suggested retail price (MSRP) is then computed using a constant 1.5 multiplier of retail price equivalent (RPE). In reality, original equipment manufacturers (OEMs) have different margin levels based on the vehicle class, vehicle technology, or other criteria. The objectives of this project are as follows:

1. Compare the resulting differences between the current method's MSRP and the actual MSRP to better understand pricing strategies across different vehicle classes and technologies. It is likely that diverse margin levels are applied depending on electrification level or class category.
2. Using technical data collected by Argonne, carry out careful vehicle feature selection to develop a statistical model that can estimate vehicle MSRP and a machine-learning-based model that can predict vehicle MSRP. To provide maximum benefits, both methods will be used.
   A. Statistical methods have the advantage of retaining a level of interpretability from which the effect of each feature on the MSRP can be understood and analyzed and new equations can be designed; this transparency is usually lost when using machine-learning methods. In addition, statistical models naturally deliver levels of confidence around cost estimates. The resulting confidence interval could replace the arbitrary cost multiplier currently used to differentiate between low, medium, and high cost uncertainties.
   B. On the other hand, machine-learning models focus and have superior predictive power but at the cost of simplicity and interpretability loss.
3. Make use of unsupervised learning methods to infer, from data only, the cost proportion each component represents in the total vehicle cost. This will open the door to developing new component cost equations.
4. Use objective #2 to derive vehicle cost per mile ($/mile) estimates for vehicle technology, and use objective #3 to derive component-level $/mile estimates to explore the tradeoffs between the introduction of more efficient vehicle technologies (powertrain level) or more efficient component technologies—and the added cost. Connecting those estimates with sales data will enable understanding of technology's value to the customer.

Approach

This project takes a data-driven approach, and therefore its success depends on the richness and quality of the data in hand. For that vital reason, Argonne has expended considerable effort to develop an internal vehicle attribute database by leveraging web-scraping techniques to collect publicly available data.

After detailed processing, the data are used during a phase of cohort analysis; this led to the application of clustering methods to segregate the vehicles by selected criteria. This phase is essential because the MSRP distribution shows a heavy right skewness. In addition, several vehicles within the data share similar powertrain-related features but differ in MSRP value because of branding or other factors. DOE studies and vehicle analyses must remain agnostic to this level of detail (i.e., the goal at this stage is to automatically identify and classify base, luxury, performance, and prestige vehicles for proper modeling of the DOE vehicle segment of interest).

The ongoing work focuses on MSRP modeling and estimate accuracy, as well as the usability of its integration into the Autonomie system. In particular, ensemble algorithms based on gradient boosting, such as XGboost, CatBoost, and LightGBM, are currently being evaluated. Those methods have shown superior results in regression problems in several different applications. Standard neural network and random forest models are also being used and compared against boosting algorithms.

Results: Data Collection

Because this project takes a data-driven approach, Argonne has expended considerable effort expanding its internal vehicle attribute database. The research team focused especially on developing a general, automated data-collection and web-scraping process to efficiently collect vehicle data. The process allows researchers to efficiently crawl the web by deploying a web spider that targets vehicle and OEM websites. Vehicle specifications and publicly available information (including vehicle MSRP) is fetched and stored in a non-relational database (Mongo Database, aka MongDB), resulting in an exhaustive dataset that can be used to build a vehicle MSRP estimation model.

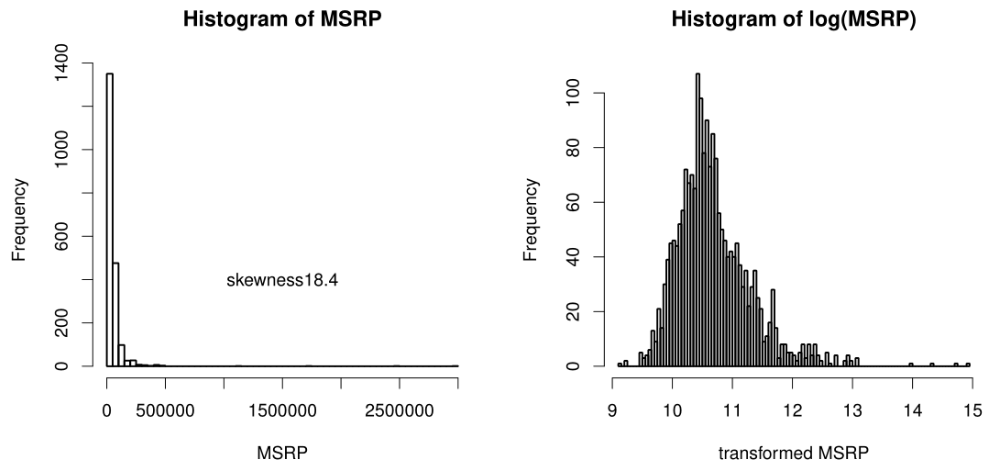

Figure I.19.1 Raw right-skewed MSRP distribution (left), log transformed (right)

Argonne completed several data processing steps:

- Cleaning – Data have been prepared for missing values and checked for inconsistencies.
- Integration – Data from various sources have been successfully integrated into a large dataset.
- Modification – Outliers have been identified and fixed using imputation methods.
- Transformation and feature engineering – Several additional calculated fields were created.
- Analysis and interpretation – Several rounds of data analysis were performed.

The database contains an extensive list of vehicle features: power specifications, drivetrain information, measurements, instrumentation, interior and exterior options, entertainment components (such as sound systems/speakers, screens, and other things that can affect vehicle pricing), and detailed information about tires and wheel specifications (type, width, aspect ratio, diameter, load index, speed rating, etc.).

VTO interest is to construct a model for which the MSRP estimation is driven primarily by powertrain components rather than other “luxury” features. However, to reduce model variance and uncertainty, some non-powertrain features will be included in the modeling; basic/standard attributes will be used as input during prediction time to reflect Autonomie “standard/average vehicle” levels.

The dataset currently includes vehicles from 1990 to 2020, with ~50,000 vehicles of various makes, models, and trim levels. About 110 variables have been selected for analysis. A study is ongoing to carefully select features and assess feature importance, in order to understand degrees of correlation with MSRP (Figure I.19.2, right). Note that 31 variables are numeric (e.g., engine power), 44 are categorical (e.g., transmission type), and 23 Boolean (e.g., engine has turbo T/F). Figure I.19.2 (left) shows a snapshot of data completeness (91% complete). Most missing values are not applicable to the vehicle in question or occasionally belong to pre-2000 vehicles, where complete data is difficult to find.

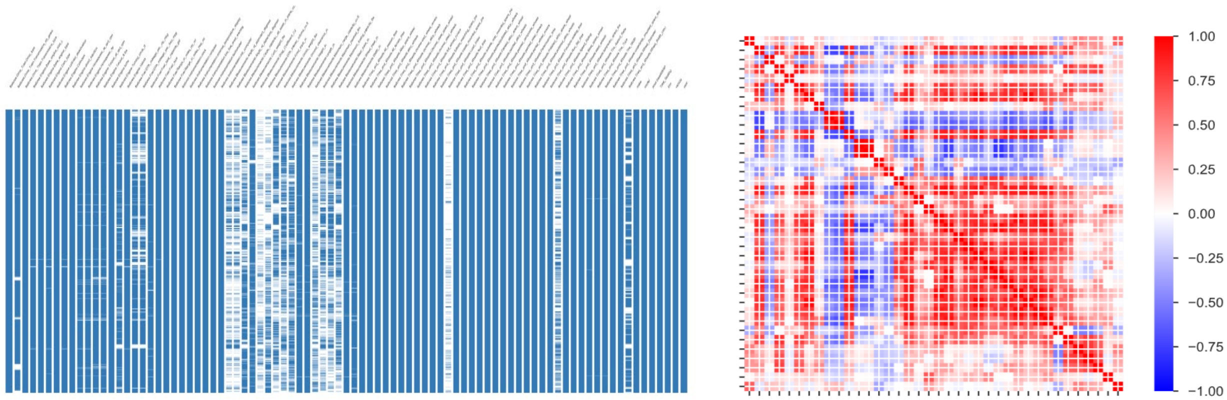

Figure I.19.2 Missing value matrix (left) and feature correlation analysis (right)

Results: Vehicle Clustering

As stated above, DOE is interested in estimating vehicle segments related to the baseline segment. This is in line with Autonomie practice and its vehicle models, which represent the “average” market vehicle for each powertrain. To segregate base, luxury, performance, and prestige vehicles for proper modeling without knowledge about the brand or trim level, a clustering approach is needed.

A series of clustering algorithms have been put to the test, but the simple and interpretable hierarchical clustering method gave notable results. The hierarchical clustering method considered groups data points using a bottom-up approach (agglomerative) based on selected features as a measure of similarity. The main assumption is that vehicles of comparable size, performance, and other carefully selected specifications (e.g., vehicle weight, wheel radius) should be comparable in price and therefore should be clustered together. The effect of this assumption is that inter-cluster vehicles with significant price differences represent different carlines (e.g., luxury).

The advantage of the hierarchical clustering method is the ability to visualize the resulting tree-based division using a dendrogram to facilitate interpretability. In addition, there is some theoretical support for an optimal number of cluster choice, a task that is always difficult to achieve in unsupervised clustering algorithms. Figure I.19.3 shows the resulting dendrogram (left) and the clustering three-dimensional projection form. This is achieved by using t-distributed stochastic neighbor embedding (t-SNE) dimensionality reduction technique (right).

The bottom plot identifies clusters by vehicle class, which reveals additional details. Within each class, a clear separation is identified between base and luxury vehicles (cluster 1 versus 2). Interestingly, a third cluster emerges from the method for larger vehicles (pickups). Where no within-class discrimination is apparent, this seems to support the fact that all pickups usually belong to one carline (a clear small variance in MSRP for pickups is also seen). Clusters 4 and 5 represent exceptionally pricey vehicles, which are eliminated from the analysis and dataset.

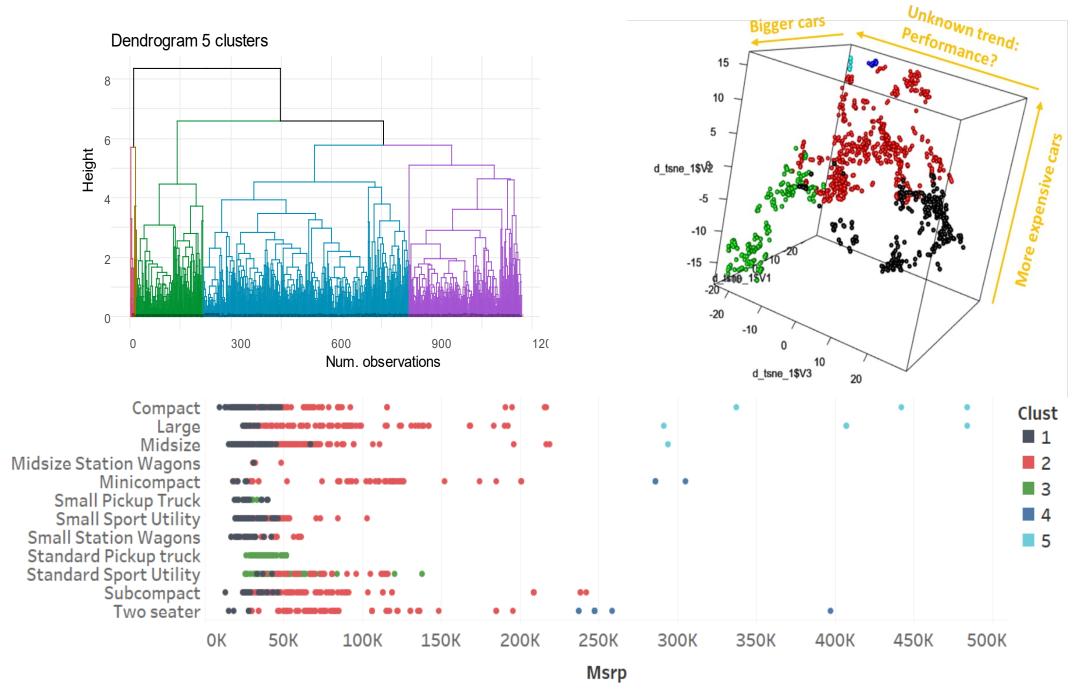

Figure I.19.3 Hierarchical clustering dendrogram (left), t-SNE (right), per class interpretation (bottom)

Finally, the data are split as shown in Figure I.19.4, where vehicles from clusters 1 and 3 are combined into one dataset to represent base vehicles (~\$0–\$80,000) and cluster 2 represents the luxury carline (~\$30–\$240,000). This method allows a soft price margin for segregation, and hence the overlap.

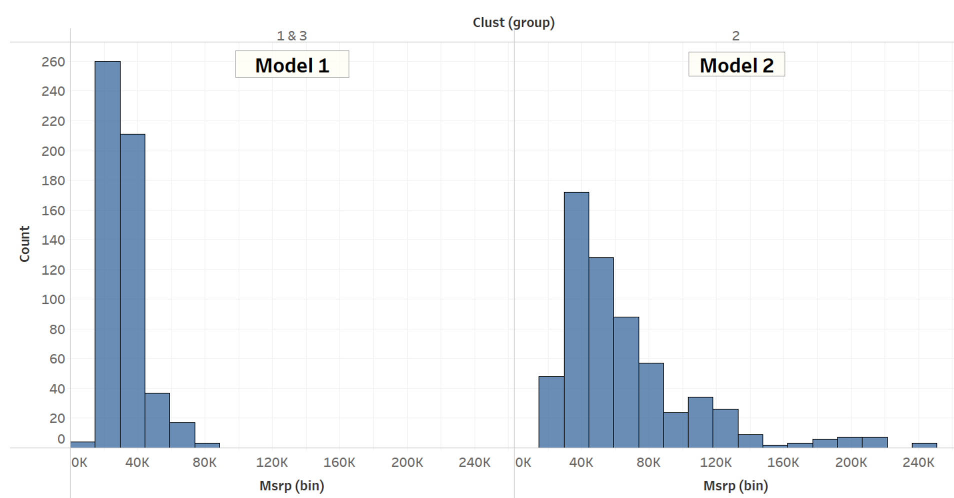

Figure I.19.4 Base carline (left) and luxury carline MSRP

Conclusions

In this first part of the project, Argonne developed a web-scraping process to efficiently collect vehicle data. The web spider was deployed to crawl several webpages, automatically fetch publicly available vehicle information, and store features of interest in a non-relational (no SQL) Mongo database. The database contains very detailed information about vehicles from 1990 to 2020.

Argonne also performed extensive data analysis, including cleaning and integrating data, to better prepare the data for modeling, as well as to understand market trends.

Finally, a clustering approach was used to segregate base and luxury carlines prior to building an MSRP estimation model. This stage provides good representative data that are then used to build a model that suits DOE vehicle segmentation (i.e., average/base market vehicles).

The ongoing work focuses on MSRP modeling and estimate accuracy, as well as usability and integration into Autonomie.

Key Publications

The project is ongoing.

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I.20 Minimum Viable Model

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Project Introduction

Transportation modeling is a critical part of the effort to understand the future of mobility. Traditional methods for performing this modeling have required heavy investment in development and computing resources. However, refining the approach to focus on the specifics of the questions being asked and considering the relative uncertainty of the assumptions can lead to much more focused approaches, helping to answer relevant questions with much less modeling overhead.

This project is a scoping study to look at questions, options, and methods for creating a minimum viable model (MVM) necessary to answer transportation modeling questions.

Objectives

Idaho National Laboratory, National Renewable Energy Laboratory, and the Texas A&M Transportation Institute are developing a framework that can be used to develop minimum viable models for future transportation research.

The objective is to create a framework that can ease the use of different approaches for specific types of problems. For instance, future vehicles and scenarios—from aerial drones and automated package delivery vehicles to automated electric passenger cars, buses and long-haul trucks—will have distinct operating profiles that may significantly alter traffic patterns, congestion, and transportation energy consumption. The impacts of these technologies, however, are dependent on adoption rates and traveler mode choice, both of which are highly uncertain. Instead of a detailed view of one scenario, answers to these types of questions may need rapid assessment of hundreds, if not thousands, of possible adoption and utilization scenarios in numerous cities and regions.

To help address this different type of need, the team will develop an action plan for creating a transportation MVM toolbox that is capable of creating more efficient models to answer questions such as the state-, regional-, and national-level impact assessment of ACES technology and trends for the movement of people and goods. The team will issue a detailed plan for model scope, development, and implementation.

Approach

To begin, the project team will identify the potential scope of modeling questions for future efforts. The team will then work to prioritize questions that will be valuable in meeting Vehicle Technologies Office Analysis Program goals.

The teams will then conduct an independent review of current modeling approaches and tools and review their sufficiency to address priority questions. This stage will include conventional modeling approaches employed by the transportation planning community, as well as advanced approaches being developed by national laboratories and academia. This task will include literature review and expert interviews.

In parallel with the review of modeling practices, the team will work to create a catalog of available data sources to support transportation modeling. Through this exercise, use of nontraditional data sources for developing travel models will also be explored.

In particular, the advancement of machine learning techniques presents an opportunity to enhance transportation modeling, both within components of specific travel demand modeling tools, as well as at the aggregate level. Thus, the team will investigate the appropriate use of machine learning to enable rapid development of scalable models.

Finally, the team will establish a plan for developing and implementing an MVM toolbox, based on findings from previous tasks. The project will issue a report that includes the goals and capabilities of the MVM approach related to the priority questions, and a plan for developing and implementing the MVM capabilities.

Results

The team has begun reviewing different elements of the transportation modeling approach, including categorizing key questions, examining the process for creating a toolbox framework for MVM, and performing a literature review of how machine learning can be applied for both mode choice and traffic assignment.

Proposed Framework for MVM

The proposed MVM framework begins with understanding the key questions that need to be addressed, and then uses a toolbox approach to determine the best modeling process. In other words, rather than proposing a single new model, the MVM team is proposing a modeling platform that allows for selection from multiple models and approaches to answer the research or policy questions of interest. The basic process will be to build from questions needed, then examine the toolbox for models, improvements, and data sources, and from these choices create a modeling approach.

This toolbox process uses traditional models, machine learning models, and data-driven approaches that are organized in parallel as options for consideration. These are mapped to the research or policy questions each model or analytical approach is most suitable to answer. The actual modeling computation can be conducted either via a query of pre-run scenarios from prior analyses or via on-demand runs. The process can also be deployed in a serverless environment through automated pipelines to maximize scalability and speed. This implementation is model-agnostic and data-agnostic, making it a neutral workbench on which all prior modeling capabilities can be utilized.

Figure I.20.1 shows a view of how the proposed framework could be implemented.

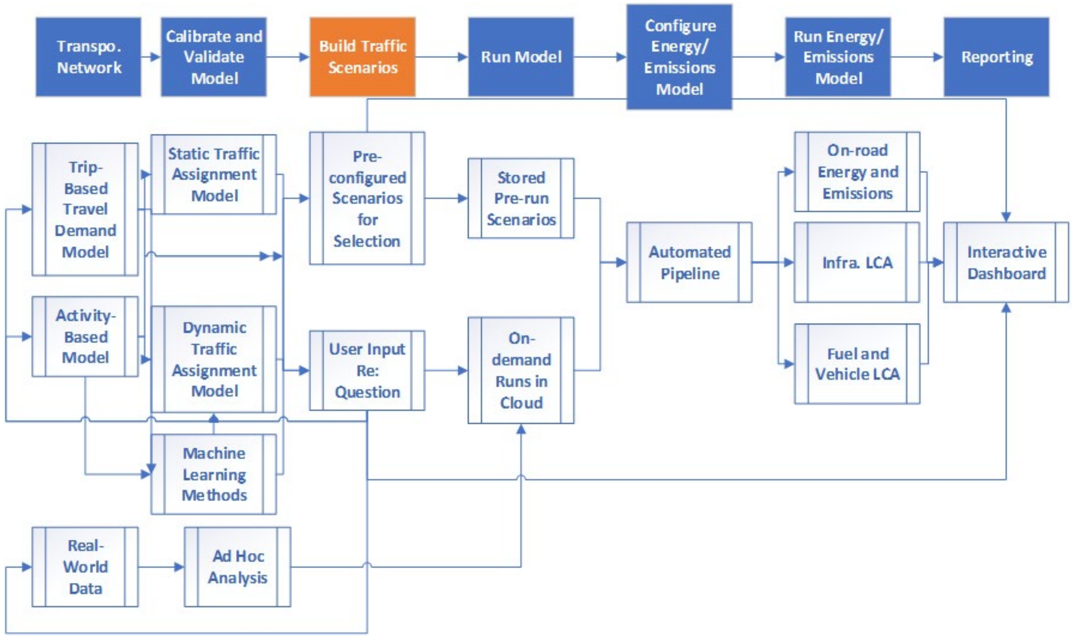

Figure I.20.1 MVM toolbox approach implementation
Source: Texas A&M Transportation Institute

Literature Review: Using Machine Learning for Travel Modeling

The team completed reviews of several current modeling approaches and data sources. In particular, the team began by reviewing BEAM and POLARIS modeling pipelines to understand the key "choice" components used in these models. While each model has its unique way of modeling travel patterns, Mode, Destination, and Departure Time Choice emerged as the key components that are common to both these models.

The team focused on ways to improve specific modeling components and began a literature review on the use of machine-learning-based approaches for mode choice modeling, destination and departure time choice modeling, and traffic assignment. Machine learning model types used for mode choice modeling include artificial neural network, decision tree, support vector machine, and naïve Bayes. These models are comparable with traditional multinomial logit (MNL) or nested logit (NL) mode choice models. Exploratory variables used in both machine learning and logit mode choice models mainly include trip characteristics, socio-demographic information (household and individual), and land use data. To help develop these models, all of the studies reviewed relied on traditional travel diary data for mode choice modeling.

Several of the key algorithms associated with traffic assignment are presented in the table below. As shown in the table, major existing modeling approaches have not taken advantage of machine learning techniques. However, further literature review reveals that machine learning techniques are receiving growing interest.

Table I.20.1 Examples of Machine Learning Traffic Assignment Models

Model	Traffic flow abstraction level	Simulation time scaling with total number N of links in all trips	Runs on high-performance computing infrastructure	Simulation time for a large city
DynusT	Explicit vehicle following and intersection models, temporal resolution of 6 seconds	O(*Nln(N)*)	No	30 hours

DTALite	Explicit simulation of vehicle queues on each link; finite difference solution of the kinematic wave equation for congestion shock waves	O(*Nln(N)*)	No	3 hours with specialized shared memory on cloud
Mobiliti	Event-driven approach; events are vehicles entering and exiting links; fast heuristics for computing the link dwell times; massively parallel implementation	O(*Nln(N)*)	Yes	1 minute using 1000 cores on high-performance computer

Several studies have demonstrated the use of machine-learning techniques for traffic speed forecasting. Notable examples include long short-time memory (LSTM) (Ma et al., 2015) and Diffusion Convolutional Recurrent Neural Network (DCRNN) (Li et al. 2017).

Conclusions

There is strong evidence that focusing on question objectives and using machine learning and novel data approaches can result in an enhanced MVM framework—one that provides vastly improved modeling scenarios that can address specific questions much quicker.

Review of machine-learning models shows that these models outperform traditional discrete choice models in capturing mode choice behavior, but the degree of improvement in prediction accuracy is very context-specific. Given the high uncertainty and complexity of hyperparameter tuning, as well as the diversity of datasets, it is difficult to determine which modeling approach (among the family of machine-learning models) is best suited for mode choice modeling.

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