U.S. DEPARTMENT OF

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Analysis Program

2020 Annual Progress Report

Vehicle Technologies Office

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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

21CTP	21st Century Truck Partnership
AC2G	Cradle-to-grave
ACES	Automated, connected, electric, or shared vehicles
ADOPT	Automotive Deployment Options Projection Tool
AEO	Annual Energy Outlook
AFV	alternative fuel vehicle
AMBER	Advanced Model Based Engineering Resource
ANL	Argonne National Laboratory
ARB	California Air Resources Board
AVCEM	Advanced Vehicle Cost and Energy-use Model
AVMT	Annual vehicle miles of travel
BA	Balancing Authority
BEAM	Behavior, Energy, Autonomy, and Mobility model
BETO	Bioenergy Technologies Office
BEV	battery electric vehicle
BISG	Belt-integrated starter generator
BPD	Barrels per day
CAFÉ	Corporate Average Fuel Economy
CAV	connected and automated vehicle
CCS	carbon capture and storage
CNG	Compressed natural gas
CO_2	carbon dioxide
DCFC	direct current fast charger
DOE	U.S. Department of Energy
DOT	U.S. Department of Transportation
EDT	Electric drive technologies
EEMS	Energy Efficient Mobility Systems Program
EERE	Energy Efficiency and Renewable Energy
EIA	U.S. Energy Information Administration
EPA	U.S. Environmental Protection Agency
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
FOTW	Fact of the Week
FY	fiscal year
GEM	Grid-Integrated Electric Mobility Model
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Transportation model
GWh	gigawatt hour
H2A	Hydrogen Analysis Production Models
HDV	heavy-duty vehicle

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HEV	hybrid electric vehicle
HFTO	Hydrogen and Fuel Cell Technologies Office
HWFET	Highway Fuel Economy Test
ICE/ICEV	Internal combustion energy vehicle
ISATT	Integrated Systems Analysis Technical Team
ISG	integrated starter generator
kWh	kilowatt hour
LCA	Life cycle analysis
LCOD	Levelized cost of driving
LDV	light-duty vehicle
MA3T	Market Acceptance of Advanced Automotive Technologies Model
MDHD/MDHDV	Medium- and Heavy-duty Vehicle
MEP	Mobility energy productivity
M-HEV	micro and mild hybrid technologies
mpg	miles per gallon
mph	miles per hour
MSRP	manufacturer's suggested retail price
Mt	Metric Tons
MY	Model Year
NEAT	Non-Light Duty Energy and GHG Emissions Accounting Tool
NHTS	National Household Travel Survey
NHTSA	National Highway Traffic Safety Administration
NREL	National Renewable Energy Laboratory
OEM	Original equipment manufacturers (OEMs)
ORNL	Oak Ridge National Laboratory
PDF	Portable Document Format
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
R&D	research and development
RE	renewable energy
SAEV	Shared, automated electric vehicles
SMART	Systems & Modeling for Accelerated Research in Transportation
SOC	State of Charge
SOV	Single-occupancy vehicle
SUV	Sport utility vehicle
TCO	Total Cost of Ownership
TDP	Transportation Data Program
TEEM	Transportation Energy Evolution Modeling
TNC	Transportation network companies
TRB	Transportation Research Board (Annual Meeting)
U.S. DRIVE	Driving Research and Innovation for Vehicle efficiency and Energy sustainability
UDDS	Urban Dynamometer Driving Schedule
VMT	vehicle miles traveled
VTO	Vehicle Technologies Office
xFC	Extreme fast charging

CH ₄	Methane
N ₂ O	Nitrous Oxide
NO _x	Oxides of Nitrogen
SO_2	Sulfur Dioxide
VOC	Volatile Organic Compound
CO	Carbon Monoxide
PM ₁₀	Particulate Matter with diameters equal to or less than 10 micrometers
PM _{2.5}	Particulate Matter with diameters equal to or less than 2.5 micrometers
BC	Black Carbon
OC	Organic Carbon

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Executive Summary

During fiscal year 2020 (FY 2020), 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 2020. 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 day¹—and move people more than 3 trillion vehicle-miles.² Growing our economy requires transportation, and transportation requires energy. The transportation sector accounts for about 30% of total U.S. energy needs³ and the average U.S. household spends over 15% of its total family expenditures on transportation, making it the most expensive spending category after housing.⁴

The Vehicle Technologies Office (VTO) funds a broad portfolio of research, development, demonstration, and deployment (RDD&D) projects to develop affordable, efficient, and clean transportation options to tackle the climate crisis and accelerate the development and widespread use of a variety of innovative transportation technologies. The research pathways focus on electrification, fuel diversification, vehicle efficiency, energy storage, lightweight materials, and new mobility technologies to improve the overall energy efficiency and affordability 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 accelerate sustainable transportation technologies 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 RDD&D barriers, and accelerate progress. VTO focuses on research that supports DOE's goals of building a 100% clean energy economy, addressing climate change, and achieving net-zero emissions no later than 2050 to the benefit of all Americans.

Annual Progress Report

As shown in the organization chart (below), VTO is organized by technology area: Batteries & Electrification R&D, Materials Technology R&D, Advanced Engine & Fuel R&D, Energy Efficient Mobility Systems, and Technology Integration. 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) 2020. In this APR, each project active during FY 2020 describes work conducted in support of VTO's mission. Individual project descriptions in this APR detail funding, objectives, approach, results, and conclusions during FY 2020.

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 10.1 Average Annual Expenditures of Households by Income, 2016.

Organization Chart

Vehicle Technologies Office

March 2021



Analysis Program Overview

Introduction

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Achieving deep decarbonization in transportation will require vehicle efficiency improvements, low lifecycle carbon-intensity fuels, and overall system-wide improvements in the transportation system. VTO funds research, development, demonstration, and deployment (RDD&D) of new, efficient, and clean mobility options that are affordable for all Americans

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:

- Which vehicle use domains---including vehicle design, powertrain technologies, increased automation, and a better understanding of travel patterns---offer the potential to provide clean mobility benefits and at a reasonable cost to both businesses and the consumer? In which applications can specific 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 charging infrastructure needs? How will use of these vehicles impact the electricity grid, and vice versa? How can this infrastructure be made available to consumers across the income spectrum, and how might the infrastructure best address the needs of individuals living in a variety of different housing/neighborhood types?
- As demand for freight transportation grows, how can we improve the efficiency of moving the goods we buy? How can a variety of medium- and heavy-duty vehicle technologies---including advanced lightweight materials, advanced engine designs, and electric powertrain technologies---help the nation to achieve key energy and environmental goals despite this demand growth?
- 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 of our subprogram targets? What if our subprograms fall short?

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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.

State of the Art

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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.

Data	 Create and maintain a strong foundation of reliable, up-to-date, and easily accessible data Provide insight into transportation and energy use for a broad range of internal and external stakeholders 		
	 Transportation Energy Data Book Fact of the Week E-Drive Data Vehicle Technology Market Report 		
Modeling and Simulation	 Build and maintain relevant analytical models supportive of techno- economic analysis Quantify outcomes in terms of efficiency, affordability, resiliency, and security 		
	 MA3T ParaChoice VISION, NEAT GREET[®] AVCEM Household-level Market Dynamics Fuel Economy Calculator 		
Applied Analysis	 Applied Analysis Provide insights into critical transportation energy problems through integrated analyses Provide inputs and metrics for program planning, budget justification, and program evaluation 		
	 Prospective Benefits Analysis Baseline and Scenario Vehicle Performance Charging EVs in Smart Cities Integration of BEAM and PLEXOS[®] Applied Analysis of CAV Technologies 		

For FY 2020, 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 2020 Annual Progress Report and the EEMS FY 2020 Annual Progress Report.

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Analysis Program Project Portfolio

Total Cost of Vehicle Ownership 1.1

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Start Date: October 1, 2019 Project Funding: \$510,000

End Date: September 30, 2020 DOE share: \$510,000

Non-DOE share: \$0

Project Introduction

The Vehicle Technologies Office (VTO) funds research and development to advance innovative technologies that will support affordable, secure, reliable, and efficient transportation systems. In particular, new vehicle technologies make vehicles more efficient to drive and more affordable to own. A comprehensive and consistent approach to estimating vehicle ownership costs is therefore of interest to VTO. A total cost of ownership (TCO) metric enables an objective and consistent assessment of the affordability of vehicles with different technologies, which can inform decisions about research and can help elucidate how vehicle technologies can improve affordability in different vehicle applications, from private, light-duty, passenger vehicles to commercial, medium- and heavy-duty vehicles.

Objectives

The objective of this project is to develop and assess a TCO metric that is comparable across powertrains and applicable to different size classes. We estimated components of ownership costs for multiple different vehicles representative of light- and heavy-duty vehicles that are on the road today and expected to be available in the future.

Our focus is on direct, monetary costs incurred by owners of light-duty passenger vehicles and owners/operators of light-, medium- and heavy-duty commercial vehicles with different powertrains. Direct costs have been quantified at a national level (averages or representative values) from the perspective of a rational vehicle owner. No "soft" costs, such as value of driver preferences for comfort, performance, styling, etc., and no costs external to purchasing and operating the vehicle, such as costs due to congestion, pollution, or noise impacts are included.

We developed estimates of all relevant cost components by collecting and analyzing data and established a firmer basis for costs such as maintenance and repair, insurance, depreciation, and some operating costs for commercial vehicles. Such data were previously available for specific makes and models, but had not been systematically and consistently analyzed in a manner sufficient to support general comparisons of these costs across powertrains for different vehicle size classes. Previous work on ownership costs have made different assumptions about many of these factors, often without a firm technical basis. We also provided a firmer basis for economic and financial assumptions, including appropriate rates for discounting, inflation, and vehicle loans.

Approach

We have collected data on vehicle prices, fuel economy, financing, fuel prices, insurance, maintenance and repair, taxes and fees, interest rates, inflation, and other operational costs from publicly available sources including literature and web sites. We selected these cost components as being appropriate to "rational" vehicle owner/operators (private or commercial) after carefully considering what costs are relevant from different possible perspectives. To the extent possible, we determined costs as functions of vehicle age, vehicle miles driven (VMT), and powertrain type for each of the light-duty vehicle (LDV) and medium- and heavy-duty vehicle (MDHDV) classes listed in Table I.1.1. Vehicle fuel economy and purchase price were estimated from the results of previous vehicle simulations [1],[2]. Costs were estimated for current vehicles and simulated future vehicles in years out to 2050.



Table I.1.1 Size Classes Included in TCO Analysis

We found few comprehensive vehicle TCO studies in the literature. Most are focused on LDVs. Many of these neglect some important cost components or make simple assumptions about costs such as depreciation, maintenance, repair, and operational costs unique to commercial vehicles. We held two workshops to collect information and to vet our approach and assumptions about commercial vehicle costs, one with vehicle manufacturers and industry experts, and one with fleet associations and experts in fleet operations. We collected and analyzed light-duty vehicle (LDV) resale values for recent model year (MY) vehicles from Edmunds "True Market Value" [3] and for medium- and heavy-duty commercial vehicles (MDHDVs) from publicly available sources. For light-duty BEVs and PHEVs, we modeled the ratio of resale value to MSRP minus the federal tax credit, as suggested by [4]. Scheduled maintenance, based on owner's manuals, and datasets on vehicle repair frequency and costs as a function of vehicle age, miles driven and time from Edmunds "True Cost to Own", YourMechanic, Utilimarc, and Consumer Reports were analyzed by size class and powertrain type [5], [6], [7], [8]. Insurance costs, based on data from Edmunds, were analyzed to estimate premiums for passenger cars, SUVs, and pickup trucks as a function of vehicle, and insurance costs for freight trucks and transit buses were also estimated from quotes [9] and industry data [10]. Information on vehicle taxes, fees, tolls, and parking costs were collected and nationally-representative estimates were developed for these for LDVs by powertrain and for medium- and heavy-duty commercial vehicles. We assumed national averages for vehicle miles traveled and vehicle survival, based on information from EPA and U.S. Census Bureau [11], [12].

We developed estimates of costs for each of the components listed in Table I.1.2 as functions of the inputs listed. The vehicle cost includes the cost of purchase less the residual value of the vehicle at the end of the analysis window. Financing represents the cost of interest payments beyond the retail price of the vehicle. Fuel cost is proportional to the driving distance and based on the price of the specific fuel used in the vehicle modeled. Insurance costs represent a national average of costs for a typical driver, including coverage for both liability and vehicle repair. Taxes and fees include taxes on vehicle sales as well as any recurring annual costs, such as registration fees, parking, and tolls. Maintenance includes the cost of scheduled vehicle repairs as the vehicle ages, while repair accounts for unexpected costs to run the vehicle. For heavy-duty vehicles, maintenance and repair are combined due to a lack of disaggregated data. Operational expenses include adjustments in fleet vehicle driving due to new vehicle technologies (e.g., a lower payload capacity, in some cases). Labor costs are representative of the typical wages and benefits for drivers. For light-duty vehicles used as household vehicles, operational and labor costs are both zero.

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Cost Component	Key Inputs
Vehicle	MSRP, Powertrain, Size class, Battery size, VMT, Performance
Financing	MSRP, Finance terms
Fuel	Powertrain, MY, VMT
Insurance	MSRP, Size class, VMT
Taxes & Fees	MSRP, VMT, Powertrain, Size class, Weight
Maintenance	Powertrain, Size class, VMT
Repair	MSRP, Powertrain, Size class
Labor	VMT, Fuel
Operational expenses	VMT, MSRP, Weight, all others

Table I.1.2 Cost Components and Dependencies

For light-duty vehicles, we analyzed TCO for the following powertrain types: Conventional internal combustion engine vehicle (ICEV), Hybrid electric vehicle (HEV), Plug-in hybrid electric vehicle (PHEV), Battery electric vehicle (BEV), and Fuel cell electric vehicle (FCEV). These same powertrains were evaluated for medium- and heavy-duty commercial vehicles. Costs and fuel economy for future vehicles were modeled using Autonomie while today's vehicles were modeled with Autonomie and compared with real-world data.

We estimated cash flows for each year of vehicle ownership within a selected time horizon (up to 15 years) in real 2019 dollars. We analyzed costs for vehicles purchased, both in cash and financed, using, in the case of the latter option, a discount rate appropriate for opportunity cost and applicable loan interest rates given by the Federal Reserve Board [13]. Present values of costs over selected time horizons and annualized costs per mile were calculated for different size classes and powertrains for current vehicles and for simulated future vehicles.

Results

Results of our analysis of LDV resale values show that over MYs 2013–2019, BEVs and PHEVs depreciate more quickly than do comparable HEVs and ICEVs. From limited data, it appears that FCEVs may also depreciate faster, as shown in Table I.1.3. However, we observed that BEVs and PHEVs of MY2017–2019 retain slightly more value than comparable ICEVs and HEVs when the effect of the federal tax credit is accounted for. Luxury LDVs depreciate at a rate similar to that of mass market LDVs.

Table I.1.3 Annual Depreciation Rates by Powertrain and Market Segment

	ICEV	HEV	PHEV	BEV	FCEV
Mass market	11.3%	12.1%	16.6%	19.2%	10 50/
Luxury	14.5%	12.0%	14.3%	17.4%	19.5%

We estimated an exponential model of the resale prices of each different size class of MDHDVs accounting for the influence of vehicle age and cumulative miles.

$$P(a,m) = P_0 \exp(A_i \cdot a + M_i \cdot m),$$

where P_0 is the retail price at age 0 with no mileage, *a* is the age in years, *m* is the mileage in thousands, and A_i and M_i are constants for each size class. Insufficient data were available to model influence of powertrain on MDHDV depreciation.

We modeled the annual cost of insurance, *I*, including coverage for liability, comprehensive and collision for LDVs by size class, accounting for dependence on MSRP as

$$I(MSRP) = L + k_1 * MSRP + k_2$$

where L is the liability premium (national average of 600/yr), and k1 and k2 are constants depending on the size class.

Analyzing maintenance costs of LDVs of different powertrains as a function of vehicle age, vehicle mileage and time (maintenance schedule), we found that, on average, HEV, PHEV, and BEV maintenance costs are lower than those of ICEVs. We also analyzed LDV repair costs (not including scheduled maintenance or costs covered by warranties) for cars, SUVs, and pickups by powertrain. We found that average repair costs, as a percentage of MSRP, were lower for HEVs, PHEVs, and BEVs than for ICEVs. We reviewed the limited data on repair costs for medium- and heavy-duty vehicles and developed preliminary estimates of these costs.

In our analysis of taxes, fees, parking, tolls, inspection, licensing, and other costs, we found modest differences between these costs for passenger vehicles with different powertrains. For commercial vehicles, weight considerations impact operational costs of the vehicles. The highway usage tax is applied to heavier vehicles to account for road wear. Additionally, heavier powertrains can lead to vehicles above the 80,000 lb. weight limit for most highway vehicles. This analysis includes the cost of an additional vehicle because of this reduced payload capacity, which can increase costs by as much as 18% for modeled BEV tractor trailers. Labor costs across powertrains during driving are assumed to be equal. However, the labor cost for additional time spent recharging a commercial electric vehicle was estimated based on the difference in time required to charge a BEV and the time required to refuel an ICEV and typical driver wages. Recharging labor costs can be high, depending on assumptions about whether personnel are required for the full time spent recharging.

We combined our modeled cost components to estimate TCO for LDVs and MDHDVs of different size classes for current and future years under different assumptions about ownership period (analysis timeframe), fuel prices, and VMT. As an example, Figure I.1.1 (TCO per mile of MY2025 Small SUV by Powertrain Over 15 Years) compares the estimated the 15-year TCO per mile of six different powertrain technologies for a small SUV in 2025. Projected fuel prices for 2025 to 2040 from the Energy Information Administration's Annual Energy Outlook 2020 Reference case [14], and a hydrogen price of \$9.58 per gasoline gallon equivalent (gge) in 2025, decreasing to \$5.00 per gge in 2030 and later years, were assumed.

The TCO of simulated 2025 MDHD commercial diesel vehicles of size classes and vocations listed in Table I.1.1 Size Classes Included in TCO Analysis is compared in Figure I.1.2 (TCO of Commercial Vehicles of Different Size Classes and Vocations Over 10 Years), assuming a 10-year analysis timeframe. Costs vary widely between vehicle types due in large part to the very different annual mileage driven and vehicle prices. Additionally, certain vocations have specific cost components of particular importance, such as high liability insurance costs for buses and high maintenance and repair costs for refuse vehicles.



Figure I.1.1 TCO per mile of MY2025 Small SUV by Powertrain Over 15 Years



Figure I.1.2 TCO of Commercial Vehicles of Different Size Classes and Vocations Over 10 Years

Conclusions

Our work has resulted in improved cost estimates for cost components of vehicle ownership that have not been well addressed in previous work, and our results support a more comprehensive assessment of ownership costs for a wide range of vehicles of different size classes and powertrain types, including commercial vehicles. In particular, our systematic analysis of depreciation, maintenance, repair, insurance, taxes, fees, and operational costs provides a much firmer basis for calculating TCO of current vehicles and for estimating TCO of future vehicles based on assumed vehicle price, fuel economy, and operational condition inputs, enabling a consistent comparison of costs across powertrains and size classes.

Areas for future improvement include establishing firmer estimates of commercial vehicle operating conditions and costs, better estimates of future vehicle prices, and analysis of additional use cases for additional size classes and vocations and for emerging transportation modes.

References

- Islam, E., A. Moawad, N. Kim, and A. Rousseau, 2020, Energy Consumption and Cost Reduction of Future Light-Duty Vehicles through Advanced Vehicle Technologies: A Modeling Simulation Study Through 2050, Argonne National Laboratory, Lemont, IL, ANL/ESD-19/10.
- Vijayagopal, R, D. Nieto Prada, and A. Rousseau, 2019, Fuel Economy and Cost Estimates for Medium- and Heavy-Duty Trucks. Argonne National Laboratory, Lemont, IL, ANL/ESD-19/8.
- 3. Edmunds TMV, 2020, Edmunds.com True Market Value. https://www.edmunds.com/tmv.html.
- 4. Zhou, Y., D. Santini, T. Stephens, and J. Ward (2016), "Comparison of value retention of plug-in vehicles and conventional vehicles and potential contributing factors," Paper presented at the Transportation Research Board Proceedings of the 95th Annual Meeting.
- 5. Edmunds TCO, 2020, Cost of Car Ownership. https://www.edmunds.com/tco.html
- 6. Burnham, A., 2020, AFLEET Tool 2019 Utilimarc Dataset, Argonne National Laboratory, <u>https://greet.es.anl.gov/afleet.</u>
- 7. YourMechanic, 2020, Auto Repair and Maintenance Services, Last accessed July 20. https://repairpal.com/estimator.

- Consumer Reports, 2019, Consumer Reports' Car Reliability FAQ, November 2019. <u>https://www.consumerreports.org/car-reliability-owner-satisfaction/consumer-reports-car-reliability-faq/</u>.
- 9. Progressive, 2020, Car Insurance, last accessed June 23, 2020. https://autoinsurance1.progressivedirect.com/1/UQA/Quote/
- 10. Murray, D. and S. Glidewell, 2017 An Analysis of the Operational Costs of Trucking: 2019 Update. <u>https://truckingresearch.org/wp-content/uploads/2019/11/ATRI-Operational-Costs-of-Trucking-2019-1.pdf</u>.
- U.S. EPA, 2016. Draft Technical Assessment Report: Midterm Evaluation of Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards for Model Years 2022-2025. EPA-420-D-16-900, July 2016. <u>https://www.epa.gov/regulations-emissions-vehicles-and-engines/midterm-evaluation-light-duty-vehicle-greenhouse-gas</u>
- 12. U.S. Census Bureau, 2004. 2002 Vehicle Inventory and Use Survey
- 13. Federal Reserve Board, "Data Download Program," data series for "Consumer Credit (G.19)," "Finance Company (G.20)," and "Selected Interest Rates (H.15)," <u>https://www.federalreserve.gov/datadownload/</u>.
- 14. Energy Information Administration, 2020, Annual Energy Outlook 2020: With Projections to 2050, U.S. Department of Energy, Washington, D.C., <u>https://www.eia.gov/outlooks/aeo/</u>.

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I.2 Integrated Systems Assessment Technology Team (ISATT) Analysis of Vehicle/Fuel Systems (Argonne National Laboratory)

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Project Introduction

This project uses life cycle analysis (LCA) to estimate the cradle-to-grave (C2G) greenhouse gas (GHG) emissions and cost of light-duty vehicles (LDVs) considering current and future technologies. For this analysis, Argonne National Laboratory configured the GREET[®] (Greenhouse gases and Regulated Emissions and Energy use in Technologies) model to evaluate the life-cycle GHG emissions of current and future technology pathways of the following:

- Petroleum and renewable gasoline use in internal combustion engine vehicles (ICEVs) and hybrid electric vehicles (HEVs)
- Conventional and renewable natural gas use in compressed natural gas (CNG) ICEVs
- Diesel use in ICEVs
- Corn and cellulosic ethanol use in ICEVs
- Steam-methane reforming (SMR) and renewable hydrogen use in fuel cell electric vehicles (FCEVs)
- Current and low-carbon electricity use in plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs).

Objectives

The goal of this project is to identify the C2G GHG emissions and costs associated with current and future (2035) LDV technologies, considering a variety of powertrains and fuel pathways. Utilizing gasoline-powered sedans and small SUVs in the United States as the baseline, this project evaluated not only GHG reduction potential but also the cost of those GHG reductions, using future cost projections for conventional fuels, biofuels, electricity from different resources, and hydrogen produced via several technology pathways. Vehicle-fuel combinations that offer significant GHG reductions in the most economically favorable manner can thus be identified.

Approach

This project used fuel economy, vehicle composition, and vehicle cost data from vehicle simulations using Argonne's Autonomie model for both sedans and small SUVs so that each vehicle powertrain could achieve common performance metrics for each vehicle class. In addition to estimated vehicle energy consumption, Autonomie provided manufacturing cost estimates for the vehicle using a bottom-up approach, including fuel cell, vehicle onboard hydrogen storage, batteries, electric motors, IC engines, and vehicle glider (body and chassis).

The GREET model was used to evaluate the effect of vehicle energy consumption on GHG emissions considering both the vehicle cycle (i.e., the materials within the vehicle) and the fuel cycle (i.e., the energy consumed for motive power). The fuel cycle consists of fuel pathways (e.g., gasoline, diesel, CNG, ethanol, hydrogen, and electricity) from both "conventional" technologies and energy sources (i.e., the current market approaches for these fuels) and from future low-carbon production pathways (e.g., bio-gasoline from pyrolysis, hydrogen from water electrolysis via wind or solar power, electricity from advanced combined-cycle natural gas combustion with carbon capture and sequestration for BEVs, etc.). The latest information from U.S. DOE models and the literature was used to estimate fuel costs for current and future technology scenarios.

Results

Current and future technologies were evaluated for GHG emissions and costs using both a baseline future scenario and an advanced future scenario. The baseline future scenario assumes the current technologies for fuel pathways, while the advanced scenario considers advanced biofuels and other low-carbon fuel sources, assuming that DOE performance and cost targets are achieved. GHG emissions results suggest that a significant reduction in vehicle-related GHG emissions is possible with baseline future fuel pathways, owing to potential improvement in fuel economy with the advancement in vehicle technologies. As Figure I.2.1 GHG emissions for current and future vehicle technologies considering baseline fuel pathways as well as advanced low-carbon fuel pathways. shows, further GHG reductions are possible with the use of low-carbon fuel production pathways. Gasoline and diesel from electro-fuels pathways as well as electricity from wind and solar photovoltaics offer the greatest reduction potential for GHG emissions, according to this analysis.

Preliminary results of the levelized cost of driving are being developed and indicate that, while conventional gasoline still represents a low-cost option in current and future scenarios, some advanced fuels' pathways are approaching comparable costs and offer GHG reductions over current processes.



Figure I.2.1 GHG emissions for current and future vehicle technologies considering baseline fuel pathways as well as advanced low-carbon fuel pathways.

Conclusions

Cradle-to-grave GHG emissions for current and future vehicle technologies and fuel pathways have been evaluated. The results show significant GHG reduction potential from expected vehicle technology advancement along with further reduction potential from advanced low-carbon fuels production.

Acknowledgements

The U.S. Integrated Systems Analysis Technical Team (ISATT) comprises experts from the U.S. Department of Energy, the energy and auto industries, and national laboratories. The team acknowledges the support of experts from various organizations in the ISATT team.

I.3 Update of Vehicle Manufacturing Cycle for Light Duty Vehicles (Argonne National Laboratory)

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Non-DOE Share: \$0

Project Introduction

Argonne updated its GREET life cycle analysis model with new vehicle material compositions for light-duty vehicles across the powertrain spectrum, including ICEVs, HEVs, PHEVs, BEVs, and FCEVs. Updated material compositions were developed for midsize sedans, small sport utility vehicles (SUVs), and pickup trucks. The data for this update was derived from a dataset based on vehicle teardown studies from A2Mac1, an automotive consulting company that specializes in vehicle teardown analysis. Argonne updated the vehicle component weights and material compositions for these light-duty vehicle classes and powertrain technologies so that the vehicle materials in the GREET model align more closely with the current vehicle market.

Objectives

The objective of this project is to characterize the materials currently in use in sedans, small SUVs, and pickup trucks in the U.S. market to better represent those vehicles in the GREET model. The aim is to understand the effects that these vehicle materials have across the entire life cycle of the vehicle, from vehicle manufacturing through the vehicle's use and extending to its retirement. The vehicle manufacturing stage, especially the embodied energy and emissions burdens of materials, can contribute from 10% to 35% of a vehicle's total life-cycle energy consumption, depending on the vehicle class and powertrain. Therefore understanding a vehicle's material composition is critical to having a complete picture of the energy and environmental burden posed by the vehicle.

Approach

Argonne used the A2Mac1 teardown database, which contains over 400 separate vehicle models across several worldwide markets. These teardown studies classify vehicle components to a highly disaggregate level, reporting each component's weight, the relative position of the component within the vehicle system (i.e., part of the body, powertrain, etc.), and information on the component's constituent materials. The materials data is classified into broad categories (metal, plastic, etc.), and additional details are provided for some components. The degree of detailed material information can vary by component, and the classification of materials does not always match the established material categories in the GREET model. Therefore Argonne established a

modeling approach to relate each material identified in the selected vehicles to the material types available in GREET.

A similar approach was required for material components within broad vehicle systems. Overall, the vehicles in the GREET model are classified into body, chassis, powertrain, transmission, motor, generator, electronic controller, fuel cell and hydrogen storage, and battery systems. Thus, each component within the A2Mac1 database needed to be allocated to one of those systems. The large quantity of data, and especially the categorization of materials, in the A2Mac1 database required manual interfacing to classify many materials. In order to maintain the data processing effort at a manageable level, Argonne selected a number of vehicles in the database that are relevant to the vehicle technologies under investigation by Argonne.

Results

Using the methods described above, we chose three midsize cars, four small SUVs, and three pickup trucks that have high market share to be exemplars of the US light-duty fleet. From this set of vehicles we developed an average vehicle that is representative of the market for each vehicle class. This average vehicle has detailed information on its material composition, down to the system level, in the GREET model, and we reported additional disaggregation. These were then integrated across the GREET platform for all powertrains, and now serve as the available vehicle models in GREET.





The weight of cars is less than that of SUVs, which are themselves less heavy than pickup trucks. Steel is the dominant material in these vehicles, while aluminum (wrought and cast), plastic, copper (wiring), rubber, cast iron, and glass make up most of the rest of the vehicle weight. Batteries represent a significant weight for some PHEV and BEV powertrains.

Conclusions

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The results of this project provided direct inputs to the GREET model to evaluate the environmental performance of vehicles. We saw that, compared to previous versions of GREET, the vehicle's material composition causes a small increase in the total vehicle life cycle energy use. This represents approximately a 1% increase in total energy use across vehicle classes and powertrains. While this change may not seem large, the modeled changes to vehicle material composition improves the understanding of a vehicle's total life cycle.

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I.4 Consumption-Based Regional Electricity Characteristics Database for North America (Argonne National Laboratory)

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Project Introduction

Accurately accounting for the energy use and emissions embedded in consumed electricity is crucial for regional LCA of electricity-associated processes, products, and technologies. Most electricity databases for North America (including GREET) are based on characteristics of regional electricity generation. This generation-based treatment is acceptable for relatively isolated power regions that have no or minor electricity interchanges with adjacent regions. In reality, however, regional electricity transfer for economic, reliability, and safety purposes. This implies that regional electricity characteristics may differ significantly when considered from a consumption-based perspective. In this project, Argonne developed a complete consumption-based electricity characteristic database for North America at the balancing authority and state/province/country level for 2017.

Objectives

The objectives were to (1) develop methods for and then derive consumption-based electricity mixes, energy use intensities, and emission intensities for both greenhouse gases (GHGs) and air pollutants for electricity used in U.S. states, Canadian provinces, and Mexico, (2) compare consumption-based and generation-based results at the regional level, (3) map the virtual emission flows in the North American electric grid, and (4) conduct source apportionment of electricity use and responsibility allocation for electricity/emission generation.

Approach

In North America, the regional electrical grids are operated and managed by entities called balancing authorities (BAs). To reflect the operation of the electrical network in the real world as much as possible, we developed an integrated modeling framework for the entire North American electricity network that takes into account the electricity generation, consumption, interregional electricity imports and exports, energy use, and emissions of 78 BAs (or BA equivalents) in the U.S., Canada, and Mexico. All power plants in the U.S., BAs, and geographical regions (including U.S. states, Canadian provinces, and Mexico) were treated as individual input-output-type "processes." GREET software was used to solve the complex energy and emissions

allocation of individual electricity flows among the various "processes" in the integrated North American electricity network.

A detailed inventory of energy consumption, net electricity generation, GHG emissions (including CO_2 , CH_4 , and N_2O), and air pollutant emissions (including NO_x , SO_2 , VOC, CO, PM_{10} , $PM_{2.5}$, BC, and OC) for the electric industry of North America in 2017 was developed at the plant level for the U.S., the BA level for Canada, and the country level for Mexico. A complete database of electricity transfers among all BAs in 2017 was also compiled. These data were derived from more than 30 publicly available sources.

Results

Results show that consumption-based electricity characteristics differ significantly from generation-based characteristics for most regions of North America due to frequent interregional electricity interchanges. An example of electricity mixes is shown below. There were only five states with a < 5% shift of electricity mixes and 32 states with a >15% shift. Although Canada only contributed $\sim 1.7\%$ of the electricity consumed in the U.S., it contributed 12%–22% of the electricity consumed in the northeastern U.S. (i.e., the New York and New England regions), and $\sim 5\%$ of the electricity consumed in northwestern states (e.g., Washington and Oregon).



Figure I.4.1 Generation-based (top) and consumption-based (bottom) electricity mixes by region in North America in 2017. The middle section shows differences between consumption-based and generation-based electricity mixes in percentage points.

Combining electricity interchanges and consumption-based emission intensities, we mapped the virtual emission flows within the North American electricity network. In 2017, 9.6% of GHG emissions and 6.4%–11.5% of air pollutant emissions (depending on the species) from power plants in North America were embedded in electricity interchanges and transferred inter-regionally.

Detailed source apportionment of electricity use and embedded emissions was conducted for individual regions. For example, although California's power plants emitted only 36.3 Mt of GHGs in 2017, from the consumption point of view, electricity sales in California were responsible for 60.3 Mt GHG emissions of the North American electrical grid's total. For air pollutants, virtual emissions embedded in California electricity

sales were 17% (for OC) to 1093% (for SO₂) higher than direct emissions from the power plants in California, implying more California environmental burdens from the consumption-based perspective.

Conclusions

The consumption-based electricity database improves the representation of regional electricity in North America significantly. The virtual emission flow maps help us better understand the environmental impacts of electricity consumption. The results of source apportionment of electricity use can provide insights to inform appropriate allocation of emissions of electricity production among users in consumption regions.

Key Publications

1. Lu, Z., and Elgowainy, A. 2020. Consumption-based regional electricity characteristics of North American electrical network. (In review.)

I.5 Transportation Energy Evolution Modeling

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Project Introduction

Vehicle market dynamics modeling for energy transition issues are important to the DOE mission and to its stakeholders, enabling both government and industry to better understand and quantify the future value of research and development (R&D). Technology impacts (e.g., energy consumption, consumer costs, energy security) are often used to justify and prioritize R&D investments in advanced vehicle technologies. Quantifying such impacts requires estimation of consumer adoption of the technologies. However, consumers may view technologies differently than engineers, scientists, and economists. Meanwhile, suppliers seek less risk, more market certainty, and good public image, in addition to profits. Each of these factors, both individually and in combination, 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 the Oak Ridge National Laboratory developed the MA3T (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. In the MA3T model, the key output is annual sales share of either 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 of these inputs can be easily changed in the Microsoft Excel-based model.

The success of the VTO Analysis investment in the MA3T model has been evidenced by expanded sponsorship from the International Institute for Applied Systems Analysis (IIASA), Aramco, VTO EEMS, Hydrogen and Fuel Cell Technologies Office (HFTO), Bioenergy Technologies Office (BETO) and EERE, for both adaption of MA3T for other purposes and application of it. The TEEM team has published over 80 peer-reviewed articles (https://teem.ornl.gov/publications.shtml), including 16 during FY20.

Objectives

The objectives of the TEEM/MA3T project are to: (1) develop a user-friendly, useful, and credible simulation tool in support of techno-economic analysis with respect to energy-relevant vehicle technologies; (2) close key knowledge gaps in fundamental issues, (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 MA3T model is based on a nested multinomial logit methodology, with the immediate outputs indicating the purchase probability of each technology option by each consumer segment. These probabilities are then translated into estimates of 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. Model inputs include consumer segmentation and attributes, technology cost and performance, infrastructure availability and prices, and government incentives.

The MA3T and its derivative models are structured to accept data, targets, and assumptions from VTO R&D programs, including but not limited to: program targets of VTO, HFTO, and BETO, projected energy prices from various Annual Energy Outlook (AEO) scenarios, industry inputs on battery cost and fuel economies, state-level PEV incentives, regional deployment of public chargers, and, in some cases, the hypothetical deployment of extreme fast charging. The TEEM program also developed new methods to quantify certain utility components in consumer choice, such as range limitation cost and refueling inconvenience.

In particular, to improve the future MA3T modeling assumptions, in FY 2020 the primary effort of the team was to update and calibrate the MA3T model with the most recent data sources and public literature, to capture the market dynamics impacted by the development of charging infrastructure and related technologies, and to better understand transportation energy decisions under stochastic uncertainty and the impacts of new technology trends such as micro (stop-start only) and mild (stop-start and breaking regeneration) hybrid technologies.

Results

1. Total Cost of Ownership - Energy Use and Price

For a multi-lab Total Cost of Ownership (TCO) study, the team collected data on vehicle fuel consumption and fuel price for both LDVs and MHDVs from multiple sources. In particular, it is found that fuel consumption and time consumed during idling and power-take-off (PTO) for MHDVs are significant. For example, PTO and idling can take 63% of total operation time and 21% of total energy use for utility trucks. This has implications for charging opportunities and electrification, and requires further research.

2. REVISE 2.0 Model

The team developed an integrated model (REVISE 2.0) to evaluate inter-regional national corridor charging infrastructure requirements in the U.S. considering heterogeneous travel behaviors and mode choices. The core model is a mixed integer linear programming model with stochastic chance constraint, solved using the genetic algorithm optimization method with parallel computing. Major contributions of REVISE 2.0 are three-fold. First, heterogeneous behaviors are modeled based on various demographic dimensions. Second, travelers' inconvenience cost function was quantified by linking travelers' acceptance of charging infrastructure with exogenous technology and social factors. The inconvenience cost function simulates mode choice between battery electric vehicles (BEVs) and alternative modes by heterogenous travelers. Third, the inter-regional charging infrastructure requirements were evaluated with the entire U.S. mainland interstate highway network.

3. Workplace Charging Model

The team developed an optimization model that could help service providers (e.g., companies) with workplace charging planning. This model is a mixed integer linear programming model, implemented in IBM's OPL and solved using CPLEX 12.9. The model aims at maximizing the total additional electric miles enabled by workplace recharging of employees' plug-in electric vehicles. Subject to a given annual budget, the model provides optimal planning decisions on workplace charging station setup and charger selection, and optimizes detailed workplace charging operations, e.g., charging spot assignment and charging schedule considering the temporal distribution of charging demands and varying electricity prices. Results of experiments based on national average travel data indicate that actual workplace charging strategy varies by budget level. Through optimization, a strategy can be developed that could effectively reduce the impacts of varying electricity prices, i.e., with smart charging, namely shifting charging schedules to periods when electricity prices are low.

4. Impacts of Real-World Driving Cycles on Vehicle Sales

Fuel cost is an important factor in understanding consumers' acceptance of advanced vehicle technologies. As modeled in MA3T, lab-based UDDS and HWFET driving cycles are typically used to evaluate different technologies' energy use. These are also the basis for DOE's prior benefits analysis of VTO targets for the vehicle market and for national energy use. However, lab-based driving cycles can be quite different from real-world driving cycles, and the latter is most relevant to the actual energy cost for consumers and could have a bigger impact on actual vehicle sales. It is important to understand if there is a significant difference in vehicle sales due to the different driving cycle assumptions. To explore this, the ORNL team collaborated with the ANL Polaris team to evaluate the impact of real-world driving cycles on vehicle sales. Real-world driving cycle fuel economies, by technology, were simulated using ANL's Polaris, which is based on Chicago area driving conditions, and the resulting values were input into the MA3T model in order to help estimate the vehicle market share in future years. The vehicle market shares resulting from the use of both real-world driving cycles (Polaris) and from the previously mentioned lab-based driving cycle analyses were compared to results from the DOE benefits analysis. It is found that the VTO targets provide similar savings with real-world driving cycles when compared to the benefits analysis study results.

5. Modeling the External Effects of Air Taxis in Reducing the Energy Consumption of Road Traffic

Air taxis may divert some drivers away from congested traffic corridors, improve traffic speed and fuel economy, and reduce congestion-induced energy consumption. The team has published a paper in the Transportation Research Record that attempts to quantify these effects. As the paper notes, a model was developed that links several key components: mode choice, the relationship between travel demand and traffic speeds, the relationship between traffic speeds and fuel economies, and the heterogenous value of travel time. The model was applied to the Los Angeles Downtown - LAX route, where peak-hour traffic is characterized by 38,200 vehicles attempting to pass the route with an hourly capacity of 17,200 vehicles. With optimistic assumptions and mature technologies, the study estimates that if 20% of the traffic (7,640 travelers) were to be diverted, this would lead to a significant increase in traffic speed, from 14 to 26 mph, for the other 30,560 vehicles (i.e., 80%). This, however, still far exceeds the 17,200 vehicle/hour road capacity and therefore prevents free flow (65 mph). Nonetheless, the almost doubling of the average traffic speed leads to a 46% decrease in travel time, from 78 to 42 minutes, and triples the fuel economy to 21.7 mpg. This leads to a 73.6% reduction in on-road vehicle fuel use (about 71 thousand gallons) and an added consumption of 39 MWh of electricity from air taxi operation. The key insight is that a small share of congested travelers switching to air taxi services, driven by the private benefits of time savings, can create significant external benefits for other road travelers (in both time savings and fuel savings) and to society (in the form of reduced energy use and emissions), creating a win-win-win outcome.

6. Micro HEV paper

The team has published a paper on eTransportation which is aimed at evaluating the impact of market adoption of micro and mild hybrid technologies (noted together as M-HEV) on the average fuel economy of the new vehicle fleet and on the sales share of PEVs [4]. This study reviews recent sales trends and market forecasts. In the U.S., 21% of passenger cars and 36% of light trucks had stop-start engines in 2018, figures that have increased from less than 1% in 2012. The growth of stop-start technology in light-duty trucks has been much faster than in passenger cars. At the same time, micro-HEV technology is less popular in the vehicle models produced by Japanese and Korean automakers, while it has been more common in the vehicles produced by European and American automakers. This study also uses published estimates of M-HEV under different scenarios of M-HEV choice positions, an approach designed to enhance conclusion robustness. It is found that, among engine-based powertrain choices, micro-HEV appears to be the most cost-effective, followed by ICEVs, mild-HEVs and, lastly, full HEVs. M-HEV technologies are likely to improve fleetwide average fuel economy without significant adverse effects on the sales of plug-in electric vehicles and are likely to remain highly competitive, alongside PEVs, through 2050.

7. xFC and battery degradation

The provision of extreme fast charging (xFC) could facilitate the adoption of electric vehicles, but it could also accelerate battery degradation. This effect has been studied in the lab setting but is less understood in the real world, where driving pattern, charging behavior, ambient temperature, charging power, and starting/ending states of charge come into play. The team has a working paper that explores the potential impact of xFCs on BEV degradation from the consumer cost-effectiveness perspective, taking into account the total cost of BEV ownership, range anxiety over vehicle lifetime, BEV range design and battery warranty offering. This work finds that the benefits of xFC on time saving and range extension can outweigh its negative effect on battery life.

8. US VMT-fuel economy

The team has a working paper (accepted for TRB 2021 presentation) that estimates the correlations of vehicle mileage/fuel use with vehicle class/size and household characteristics. The study provides the fuel use results by considering the possible heterogeneity of annual vehicle miles of travel (AVMT) by vehicle class/type. Some key findings are: 1) A larger-size vehicle tends to have a higher per-vehicle AVMT than a smaller-size vehicle in both the U.S. and China, and this effect is more prominent in China; 2) The heterogeneity of annual fuel consumption is highly correlated with household characteristics, such as income and household size; and 3) Explicit consideration of per-vehicle AVMT heterogeneity by vehicle class leads to higher estimates of total fuel use.

9. Maximum utilization and deployment prioritization of public charging infrastructure

To inform deployment decisions of public charging technologies, it is important to better understand the potential utilization and deployment priority of different types of charging infrastructure. A data-driven Cumulative Public Recharging (CPR) model is developed to explore the travel patterns using 2017 National Household Travel Survey (NHTS) data. Given the revealed daily trip sequence, trip distance, dwell times, and the assumptions of vehicle recharging behaviors, the study examines the daily maximum charging potentials and the resulting maxima of all-electric range under different types of charging speeds, battery capacity and charging behavior constraints. The results suggest that more advanced public chargers and high levels of charging availability increase the daily maximum driving range. Residential charging is sufficient for most daily short-distance trips while public chargers are still needed for middle and long-distance trips. xFC may not be necessary for people with home charging but could be more useful for people without it and for situations that require urgent charging. The overall conclusion is that high market penetration of Level 2 chargers and medium market penetration of DCFC should be considered priorities for deployment.

Conclusions

In FY 2020, the TEEM team conducted research on vehicle technology-related topics that investigated potential extensions of the MA3T model and that identified opportunities to improve the existing assumptions within the MA3T model. In particular, four charging infrastructure-related studies (study 2, 3, 7, and 9 in the Results section) were carried out to enable the MA3T model to represent extreme fast charging and its impact on PEV acceptance. Energy impacts of new technologies were analyzed, including air taxi and micro-HEV. More research is needed to continue the improvement of MA3T and its derivative models toward the goal of achieving fully integrated analyses of emerging energy-relevant technologies.

Key Publications

1. Ou, Shiqi, David Gohlke, and Zhenhong Lin. "Quantifying the impacts of micro-and mild-hybrid vehicle technologies on fleetwide fuel economy and electrification." eTransportation (2020): 100058.

A total of 16 FY20 publications are available at https://teem.ornl.gov/publications.shtml
References

- Ou, Shawn., He, Xin, Ji, Wenqi. et al. Machine learning model to project the impact of COVID-19 on US motor gasoline demand. Nature Energy 5, 666–673 (2020). https://doi.org/10.1038/s41560-020-0662-1
- Li, Shengyin, Fei Xie, Yongxi Huang, Zhenhong Lin, and Changzheng Liu. "Optimizing workplace charging facility deployment and smart charging strategies." Transportation Research Part D: Transport and Environment 87 (2020): 102481
- 3. Lin, Zhenhong, Fei Xie, and Shiqi Ou. "Modeling the External Effects of Air Taxis in Reducing the Energy Consumption of Road Traffic." Transportation Research Record (2020): 0361198120952791.

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I.6 Transportation Energy Data Book and Fact of the Week (Oak Ridge National Laboratory)

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Start Date: October 1, 2019 Project Funding: \$400,000/year End Date: September 30, 2020 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 Energy Data Book and Vehicle Technologies Fact of the Week are created by Oak Ridge National Laboratory's Transportation Data Program (TDP). The 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 38.1 and 38.2, and (3) produced a draft of Edition 39 of the Transportation Energy Data Book, including updated data and information.

Approach

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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.6.1). 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., Ward's 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 Word and/or Microsoft 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-factweek), 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 Microsoft Excel files for the Transportation Energy Data Book (https://tedb.ornl.gov/) are posted on the website hosted by ORNL. The major topics for the TDP publications are provided in Table I.6.1.

Discovery	Due Diligence	DOE Approval	Publication
 Content review Source identification Data collection 	 Convert units Perform calculations Confirm revisions Analyze data Study definitions Assemble notes Create graphs & tables Write text 	 VTO approval EERE approval Draft finalized 	 Post Fact on VTO site Program Fact email Update TEDB Website Respond to inquiries Request user feedback

Figure I.6.1 Approach for the transportation data program at ORNL

Table I.6.1 Major Topics for the Transportation Data Program at Oak Ridge National Laboratory

Fact of the Week Topics
Sales
Petroleum
Fuel Economy
Travel Behavior
Gasoline
Electric Vehicles
Cost to Consumer
Diesel
Import/Export
Infrastructure
Heavy-duty Vehicles
Behavior/Ownership, and More

Results

FOTW 1102 through 1153 were posted on the VTO website during fiscal year (FY) 2020 (Table I.6.2). For FY 2019, FOTW content accounted for 397,577 pageviews, or 44% of all VTO website pageviews during the fiscal year—a 68% increase over FY 2019. Of those pageviews, 370,211 were unique visits, meaning that some visitors (27,366) to FOTW content were repeat visitors. Of all VTO website visits, 54% (364,794) of VTO site visits entered the site through a Fact of the Week landing page. Fact 915, Average Historical Annual Gasoline Pump Price from 1929–2015, had the highest number of pageviews of any VTO website page— 222,128, or 25% of all website pageviews during the fiscal year. The weekly email for the FOTW began on July 27, 2015, with 50 email subscribers. As of the end of FY 2020, there were 24,763 subscribers to the Transportation FOTW newsletter.

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Table I.6.2 Facts of the	he Week Posted o	on the VTO	website in FY 2020
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Date Posted on Website	Fact Number	Fact Title
09/28/2020	<u>1153</u>	Cumulative Plug-In Vehicle Sales in the United States Reach 1.6 Million Units
09/21/2020	<u>1152</u>	Alternative Fuel Corridors Expanding Across United States
09/14/2020	<u>1151</u>	Lithium-Ion Battery Capacity for New All-Electric Vehicles Sold in the United States Reached a Record High in 2019
09/07/2020	<u>1150</u>	Trucks Moved 68% of All Freight by Weight and 73% of Freight by Value in 2018
08/31/2020	<u>1149</u>	The Cost of Charging an Electric Vehicle in the United States Averages 15 Cents per Kilowatt-Hour
08/24/2020	<u>1148</u>	Thirty-four States Produced a Total of 1.9 Billion Gallons of Biodiesel in 2018
08/17/2020	<u>1147</u>	Iowa Produced More Than One-Quarter of All U.SProduced Fuel Ethanol in 2018
08/10/2020	<u>1146</u>	Nearly 70% of Light-Duty Plug-in Electric Vehicles in the United States Were Assembled Domestically
08/03/2020	<u>1145</u>	Plug-In Electric Vehicles Are Available in Many Passenger Vehicle Size Classes
07/27/2020	<u>1144</u>	U.S. Energy Savings Due to Light-Duty Plug-In Electric Vehicle Use Estimated at 44.8 Trillion Btu in 2019
07/20/2020	<u>1143</u>	On Average, Combination Trucks Travel More Than Five Times Farther in a Year Than Single-Unit Truck
07/13/2020	<u>1142</u>	Refineries in the Americas Produce a Greater Share of Gasoline per Barrel of Crude Oil than Refineries in other World Regions
07/06/2020	<u>1141</u>	Five Different Test Cycles Are Used to Determine Fuel Economy Estimates on New Light-Duty Vehicles
06/29/2020	<u>1140</u>	Mexico and Canada are the Biggest Recipients of U.S. Petroleum Exports
06/22/2020	<u>1139</u>	Electric Vehicle Fast Charging Stations and Outlets: CCS or CHAdeMO
06/15/2020	<u>1138</u>	New Light-Duty Vehicle Fuel Economy in the United States Has Nearly Doubled Since 1975
06/08/2020	<u>1137</u>	One-Third of all Light-Duty Vehicles Produced in the 2019 Model Year Were Turbocharged
06/01/2020	<u>1136</u>	Plug-in Vehicle Sales Accounted for about 2% of all Light-Duty Vehicle Sales in the United States in 2019
05/25/2020	<u>1135</u>	Corporate Average Fuel Economy Standards Finalized Through 2026
05/18/2020	<u>1134</u>	Electricity Sources Influence Electric Vehicle Upstream Emissions
05/11/2020	<u>1133</u>	There Were Nearly 700 Vehicles per Thousand People in North America in 2017
05/04/2020	<u>1132</u>	Texas and the Gulf of Mexico Accounted for More than Half of U.S. Crude Oil Production in 2019
04/27/2020	<u>1131</u>	Average Fuel Economy for Model Year 2019 Light-Duty Vehicles Was 95% Better than Model Year 1975
04/20/2020	<u>1130</u>	Transportation was Nearly 16% of Household Expenditures in 2018
04/13/2020	<u>1129</u>	The Gulf Coast Region Had the Lowest Average Annual Gasoline Price in 2019
04/06/2020	<u>1128</u>	Innovations in Automotive Battery Cell Composition
03/30/2020	<u>1127</u>	Since Model Year 2016, Automatic Transmissions Have Provided Better Average Fuel Economy than Manual Transmissions

03/23/2020	<u>1126</u>	Fuel Economy Myths and Facts
03/16/2020	<u>1125</u>	Light-Duty Vehicles Were Produced in 14 Different States in 2018
03/09/2020	<u>1124</u>	U.S. All-Electric Vehicle Sales Level Off in 2019
03/02/2020	<u>1123</u>	Recent Growth of Vehicle Miles of Travel Occurred on Urban Roadways
02/24/2020	<u>1122</u>	Share of Driver's License Holders Age 65 and Older Has Increased
02/17/2020	<u>1121</u>	Crude Oil Accounted for the Majority of Primary Energy Imports to the United States in 2018 While Nearly Half of U.S. Exports Were Petroleum Products
02/10/2020	<u>1120</u>	U.S. Primary Energy Exports Have Risen 205% Over the Last Ten Years While Energy Imports Decreased by 25%
02/03/2020	<u>1119</u>	Monthly Trend in Light-Duty Vehicle Sales, 2019
01/27/2020	<u>1118</u>	Two-Thirds of Freight Shipped in the U.S. Was Shipped Less Than 100 Miles in 2018
01/20/2020	<u>1117</u>	The Number of U.S. Crude Oil Refineries Has Declined but Total Distillation Capacity Has Risen From 1982 to 2019
01/13/2020	<u>1116</u>	U.S. Light-Duty Vehicle Sales in 2019 Were Nearly 17 Million Vehicles
01/06/2020	<u>1115</u>	Urban Congestion Decreased from 2014 to 2018
12/30/2019	<u>1114</u>	There Are Currently About 142,000 Public Gasoline Stations in the United States
12/23/2019	<u>1113</u>	Average Annual Highway Vehicle Miles Traveled Per Capita Varies by State
12/16/2019	<u>1112</u>	The U.S. Transportation Sector Consumed 1.4 Quadrillion Btu of Fuel Made from Biomass in 2018
12/09/2019	<u>1111</u>	Annual Petroleum Production in the United States More Than Doubled from 2008 to 2018
12/02/2019	<u>1110</u>	Average Annual Gasoline Taxes Paid per Vehicle, by State, 2019
11/25/2019	<u>1109</u>	All-Electric Vehicles Have the Lowest Estimated Annual Fuel Cost of All Light-Duty Vehicles
11/18/2019	<u>1108</u>	Fuel Economy Guide Shows the Number of Gasoline Vehicle Models Achieving 45 Miles per Gallon or Greater is Increasing
11/11/2019	<u>1107</u>	Changes in Vehicle Miles Traveled Often Mirror Gasoline Price Changes
11/04/2019	<u>1106</u>	In the Last Two Months of 2018, U.S. Monthly Sales of All-Electric Vehicles Outpaced Both Plug-in Hybrids and Conventional Hybrids
10/28/2019	<u>1105</u>	Transportation Accounted for 8.8% of all U.S. Gross Domestic Product in 2017
10/21/2019	<u>1104</u>	Eighty-Four Million Shared Bike and Scooter Trips in U.S. in 2018
10/14/2019	<u>1103</u>	Diesel Averaged 44 Cents More per Gallon than Regular Gasoline in 2018
10/07/2019	<u>1102</u>	Twenty-Nine States and the District of Columbia Currently Have Laws to Reduce the Engine Idle Time of Motor Vehicles Within the State

The Transportation Energy Data Book is an on-line publication that is published once per year with two midyear updates to the tables and graphics. Although the draft of Edition 38 was delivered in fiscal year 2019, the final Edition 38 was approved by DOE and put online in January 2020. Edition 38.1 debuted online in April 2020, with 65 tables and 9 figures updated with more recent data than was published in the original Edition 38. In August 2020, another 52 tables and 11 figures were updated for Edition 38.2. The draft of Edition 39 was completed and delivered on September 30, 2020, with a total of 225 tables and 71 figures of transportation data, many with historical series going back to 1970. The three appendices contain an additional 51 tables. Edition 39 will be posted to the website once DOE has reviewed and approved the content. The Transportation Energy Data Book website has a keyword search feature to help users find the data they need quickly and efficiently in both PDF and Microsoft Excel format. In addition to enabling data access, the website 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. The Transportation Energy Data Book website had 74,221 pageviews in FY 2020, including 10,516 PDF file downloads and 5,613 Microsoft Excel file downloads. Google Scholar reports 3,480 citations for the Transportation Energy Data Book.

Data collected in the TDP have also provided input to other VTO programs and other agency models, such as MA3T, 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.

In fiscal year 2020 a small study was conducted to understand transportation energy use data when upstream energy is included for all fuel types. Including upstream energy added 24% (6.4 quads) to the vehicle fuel consumption that is published on Table 2.7 of the Transportation Energy Data Book: Edition 38. For most of the transportation modes, the share of consumption by mode and fuel type looked the same whether including upstream energy or not. However, the modes with the largest use of electricity, rail and pipeline, showed differences in fuel mix due to the high upstream energy use for that fuel. Electricity use increased by 162% when upstream energy was added. Gasoline, the second highest in percent change, increased by 28% with the addition of upstream energy. When including upstream energy, total transit rail energy use increased by 116%, commuter rail by 64%, and intercity rail by 44%. Pipeline was the only other mode with over a 30% increase. Historically, the trend with upstream energy included and without show similar trends, with a gradual widening of the gap between the two data series. The greater use of fuels that have higher upstream energy use, like electricity and gasoline, is the reason for the gap increase. As the highway sector transitions towards heavier use of electricity, the differences between including and excluding upstream energy will become more pronounced.

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

- Davis, S. and R. Boundy (2019). "Transportation Energy Data Book: Edition 39." ORNL/TM-2020/1333, Oak Ridge National Laboratory, Oak Ridge, Tennessee. [Draft completed in FY 2020. To be published in final form in FY 2021.]
- 2. Davis, S. (2020). "Transportation Energy Use: Comparison Including and Excluding Upstream Energy Use." ORNL/TM-2020/1540, Oak Ridge National Laboratory, Oak Ridge, Tennessee.

References

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 Davis, S. and R. Boundy (2019). "Transportation Energy Data Book: Edition 38." ORNL/TM-2019/1333, Oak Ridge National Laboratory, Oak Ridge, Tennessee.

I.7 Vehicle Technologies and Hydrogen and Fuel Cells Technologies Office Research and Development Programs Benefits Assessment Report (National Renewable Energy Laboratory)

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Start Date: October 1, 2019 Project Funding: \$600,000 End Date: September 9, 2020 DOE share: \$600,000

Non-DOE share: \$0

Project Introduction

The U.S. Department of Energy's Vehicle Technologies and Hydrogen and Fuel Cell Technologies Offices (VTO and HFTO) support research and development of efficient and sustainable transportation technologies that will improve energy efficiency, minimize emissions, and enable America to use less petroleum. The programs include research on batteries, electric drive technologies (EDT), combustion, materials, fuel cells, and hydrogen storage.

Objectives

The analysis in this report estimates the level of energy and emissions benefits from the continuation and success of VTO and HFTO programs.

Approach

This evaluation includes deep dive analyses into the benefits of technology improvements on the U.S. lightduty (LD) vehicle fleet and, separately, on the U.S. medium- and heavy-duty (MDHD) vehicle fleet. This report summarizes the outcomes from each of these analyses, both independently and in combination. Both analyses assume that technology improvement accomplishments today would not enter the market for five years, and thus do not include the benefits from past program research that are impacting energy and emissions today or in the near future. They only include the impact of rolling out greater technology improvements into new vehicle sales starting in 2025. And, while the analysis does not quantify the benefits after 2050, the trends suggest that benefits continue to grow.

Light-duty Vehicle Approach

The Automotive Deployment Option Projection Tool (ADOPT) was used to estimate the benefits for LD vehicles. ADOPT is a vehicle choice and stock model that estimates vehicle technology improvement impacts on sales, energy, and emissions [1]. It includes all of the existing vehicle options, estimates their sales using

extensively validated consumer preferences, creates new market driven vehicle options through time, and uses the estimated sales and additional derived data to estimate energy and emissions.

The VTO and HFTO program goals feed into ADOPT and are applied to the vehicles through time. The assumptions are represented by a "No Program" scenario that reflects the technology improvements assumed to occur without contributions from either VTO or HFTO, and a "Program Success" scenario under which VTO and HFTO program goals are realized. Technology advancements are assumed to enter the market five years after they are achieved, with a 1.5 cost multiplier to convert manufacturing costs to costs to the consumer. Key technology improvement assumptions can be found in the full report.

Light-duty Results

The benefits are estimated by comparing the national-level energy and emissions between the No Program scenario and the Program Success scenario. The ADOPT simulation starts in 2015, and it matches the historical sales trends through 2020, including the expanding hybrid electric vehicle (HEV) sales and 2% plug-in electric (PEV) sales, as shown, in Figure I.7.1, for the No Program scenario. Figure I.7.1 also shows the higher priced, high performance battery electric vehicles (BEVs), which sell to high-income households. As battery costs drop into the future, the sales trends change. From just before 2030 until 2035, there is a shift to greater expansion of HEVs, after which sales transition to an expanding plug-in hybrid vehicle (PHEV) market share.



Figure I.7.1 No Program vehicle sales by powertrain.

The No Program scenario results in petroleum consumption dropping from 8 million barrels per day (BPD) in 2020 to 5.2 million BPD by 2050. Carbon emissions drop from 1,370 million metric tons (MMT) to 958 MMT.

Next, the Program Success scenario was evaluated, with an assumption that all the VTO and HFTO program goals are achieved simultaneously. As can be seen in Figure I.7.2, while sales trends start similarly, with HEVs expanding followed by an expansion in PHEVs, there is also a distinctive shift towards greater BEV sales around 2040. By 2050, this scenario results in 15% less annual petroleum consumption and 11% less annual carbon emissions than the No Program scenario.



Figure I.7.2. Program Success vehicle sales by powertrain.

The benefit of each technology area was broken out by removing each subset of program goals, one at a time, from the full Program Success scenario. Without the battery and EDT programs, which support vehicle electrification, PHEV market share expands later, and sales no longer shift later to BEVs. By 2050, the annual petroleum consumption is 12% higher and annual carbon emissions are 6% higher. Removing the combustion program from the Program Success scenario leaves the conventional vehicles less efficient, increasing annual petroleum consumption and carbon emissions by 4%. Without the materials program, energy consumption increases by 1% and carbon emissions by 2%. Removing the fuel cell and hydrogen storage program from the Program Success scenario increases annual petroleum consumption and carbon emissions by 2%. Removing the fuel cell and hydrogen storage program from the are summarized in Figure I.7.3.





Heavy-duty Approach

A set of legacy modeling tools was used to assess VTO program benefits for Class 4-8 MDHD vehicles. This tool set includes the Future Automotive Systems Technology Simulator (FASTSim) vehicle powertrain model [2], the TRUCK payback-based market adoption model, and the HDStock MDHD vehicle stock model. For the MDHD analysis, these tools are not integrated, but rather are executed sequentially to translate component and vehicle level goals into vehicle performance (i.e., mpg), adoption rates, and future in-use fleet energy consumption and emissions.

While VTO does not have electrification component-level goals specific to MDHD vehicles, VTO's SuperTruck II initiative has diesel engine efficiency and vehicle-level freight efficiency goals. HFTO has recently established goals for long-haul tractors and Class 6 delivery trucks. These goals, in addition to recent analysis by NREL for VTO, are used to establish future vehicle characteristics as inputs to FASTSim, which then feeds into TRUCK, which in turn provides inputs for HDStock. As with the LD analysis, technologies incorporating research goals are assumed to enter the market five years after program success, with a 1.5 cost multiplier to convert manufacturing costs to consumer price. Key technology improvement assumptions can be found in the full report.

Heavy-duty Results

The preliminary Program Success scenario results represent realization of the program goals noted in the previous section. This scenario is compared to a No Program scenario derived from the latest Annual Energy Outlook (AEO) Reference Case by removing future adoption of component diesel technologies supported by VTO or HFTO research and development. The No Program scenario retains the very small penetration of alternative powertrains from the AEO Reference Case, including plug-in diesel and gasoline hybrid electric (PHEV), BEV, and fuel cell (FCEV) vehicles. The projections for each powertrain are below 0.6% of sales within each vehicle class and, when combined, account for less than 1.7% of sales within any vehicle class. However, there is no market penetration of integrated starter-generators and hybrid powertrains capable of providing propulsion and recapturing braking energy in either the AEO Reference Case or No Program scenario. However, there is some "micro-hybridization" which reduces engine idle but does not assist propulsion. As shown in Figure I.7.4, MDHD fuel consumption in 2050 under the No Program scenario consists of 83% diesel fuel, 14% gasoline, 2% natural gas, and less than 0.1% each liquified propane, ethanol, electricity, electricity, and hydrogen. Total energy demand and well-to-wheels carbon emissions decrease between 2025 and 2035 due to fuel consumption standards, but growth in travel demand overcomes these gains by 2050, resulting in a net increase relative to 2020.



Figure I.7.4. No Program: MDHD energy consumption by fuel and well-to-wheels carbon emissions by vehicle class

In the Program Success scenario, advanced diesel and hybrid vehicles are very successful, achieving 98% of the new vehicle market for sleeper tractors, 73% for day cab tractors, and 83% for 7&8 vocational trucks by 2040, and 88% of Class 4-6 vocational trucks by 2036. While the fuel economy of new diesel-powered trucks improves through 2050, shares of alternative powertrains begin to supplant these technologies after 2040. By 2050, PHEVs, BEVs, and FCEVs combined account for 38% to 55% of the market in the analyzed classes (Figure I.7.5 and Figure I.7.6). Note that in HDStock, diesel-electric hybrids are included in the diesel compression ignition (CI) powertrain. As shown in Figure I.7.7, this results in 25% less diesel consumption and 18% less CO₂ annually in 2050 relative to the No Program scenario. Emissions from Class 7&8 trucks decrease 25% to 35% between 2020 and 2050, while technology adoption in Class 4-6 offsets projected increases in CO₂ through 2040, after which emissions begin to increase due to growth in the vehicle stock and travel demand.







Figure I.7.6. Program Success: Vocational truck sales by powertrain.





Conclusions

The preliminary results for the combination of LD and MDHD program success scenarios can be seen in Figure I.7.8. By 2050, annual petroleum consumption is reduced by 18% and annual emissions by 20% from the No Program scenarios.



Figure I.7.8. Program Success: MDHD fuel consumption and carbon emissions.

Key Publications

1. Aaron Brooker, Alicia Birky, Evan Reznicek, Jeff Gonder, Chad Hunter, Jason Lustbader, Chen Zhang, Lauren Sittler, Arthur Yip, Fan Yang, Dong-Yeon Lee, "Vehicle Technologies and Hydrogen and Fuel Cells Technologies Office Research and Development Programs Benefits Assessment Report," in review for publication.

References

- Brooker, A., J. Gonder, S. Lopp, and J. Ward, ADOPT: A Historically Validated Light Duty Vehicle Consumer Choice Model, SAE Technical Paper 2015-01-0974, 2015, https://www.sae.org/publications/technical-papers/content/2015-01-0974/ (accessed September 24, 2018).
- Brooker, A., Gonder, J., Wang, L., Wood, E. et al., "FASTSim: A Model to Estimate Vehicle Efficiency, Cost and Performance," SAE Technical Paper 2015-01-0973, 2015, doi:10.4271/2015-01-0973.
- Kontou, Eleftheria, Marc Melaina, and Aaron Brooker. (National Renewable Energy Laboratory). 2018. Light-Duty Vehicle Attribute Projections (Years 2015–2030). California Energy Commission. Publication Number: CEC-200-2018-008.
- Yip, A. H., J. J. Michalek, and K. S. Whitefoot. 2018. "On the Implications of Using Composite Vehicles in Choice Model Prediction." Transportation Research Part B: Methodological 116: 163– 188. doi: 10.1016/j.trb.2018.07.011
- Johnson, C., E. Newes, A. Brooker, R. McCormick, S. Peterson, P. Leiby, R. Uria Martinez, G. Oladosu, and M. Brown. 2015. "High-Octane Mid-Level Ethanol Blend Market Assessment." National Renewable Energy Laboratory Technical Report NREL/TP-5400-63698.
- Brooker A, Ward DJ, Wang L (2013) Lightweighting impacts on fuel economy, cost, and component losses. SAE technical papers presented at the SAE 2013 World Congress and Exhibition, Society of Automotive Engineers, Detroit, Michigan. Warrendale, PA, p 10; National Renewable Energy Laboratory, Golden, CO. Report No. CP-5400-60307. http://dx.doi.org/10.4271/2013-01-0381. 16 Apr 2013.

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I.8 Applied Modeling and Simulation Analysis

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Start Date: October 1, 2019	End Date: September 30, 2020	
Project Funding: \$300,000	DOE share: \$300,000	Non-DOE share: \$0

Project Introduction

Vehicle simulation is a reliable way to predict the cost and energy consumption benefits of technology changes in automotive applications. This work relies on Autonomie,¹ the simulation tool developed by Argonne, to quantify the techno-economic benefits of technologies funded by the Vehicle Technologies office (VTO). This project integrates VTO-sourced data on component-level technology performance and cost to generate vehiclelevel meta-data based on U.S. standard driving cycles and thereby to inform other analysis activities. In addition, the Autonomie vehicle models will be used to support additional activities within VTO (e.g., life cycle analysis [LCA], economic impact, market penetration, individual component technology target development) and outside of VTO.

Objectives

The main goals of this project have been to:

- Quantify the benefit of vehicle technologies across multiple vehicle classes, powertrains, component technologies, and uncertainties (e.g., business-as-usual vs. VTO targets) to represent current and future scenarios.
- Develop a database including vehicle energy consumption, cost, and detailed component information, including power, energy, cost, efficiency, and operating conditions on the U.S. standard driving cycles.
- Write a report describing the main assumptions and results along with analysis provided through a Tableau Server.

Approach

To achieve the objectives outlined above, Argonne identified the following tasks (Table I.8.1).

Table I.	8.1 Argonne	Project	Tasks
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#	Tasks	Status
1	Update vehicle technical specifications based on feedback from industry partners.	Complete
2	Quantify the impact of specific changes in technology on the energy consumption levels of light-duty (LD) vehicles.	Complete
3	Update the vehicle-sizing algorithms to meet the performance requirements of each type of vehicle.	Complete

Update the technology progress forecast based on data expected from the National Renewable Energy Laboratory (NREL) and examine future trends in vehicle energy consumption.

4

Postponed to FY21

Concerning Task 1, for light-duty truck activities, the vehicle specifications considered for this work were already quite comprehensive, but there were some aspects that we were able to improve for model year (MY) 2020 vehicles. This included updates to the cold-start penalty, accessory loads, transmission efficiencies, and motor maps. We also updated specifications for medium- and heavy-duty (MD/HD) vehicles. Class 8 trucks were consolidated into long haul and regional, instead of multiple variants of sleeper and day-cab options. This simplified the vehicle list and also helped align it to that used for related activities such as the 21st Century Truck Partnership (21CTP) road map development. In fact, 21CTP partners reviewed and suggested minor changes in the vehicle characteristics assumed for these trucks. As a result, a new 12-speed gearbox and a new traction motor were added to Autonomie. Based on the suggestions of original equipment manufacturers (OEMs), we added a 2-speed gearbox to all electric powertrains, where a single speed reduction was found to be insufficient to meet the performance requirements. These updated vehicles were then used in this year's analysis work.

Efforts supporting Task 2 resulted in a process to identify the component-specific share of improvements to the overall vehicle's energy consumption. Prior analysis measured the combined impact of all of the VTO-funded technologies. In this task, we explored a new process to quantify the impact of achieving each technology target. The technologies considered in this work are shown in Figure I.8.1. We evaluated all combinations of these technologies and recorded the maximum and minimum improvements observed for each technology. For future work, we have proposed to evaluate the justifiable cost of technology improvements to aid in forming cost targets that correspond to improvements in component efficiencies, weight, energy density, etc. The scope of Task 2 was limited to mid-size LD vehicles this year; future tasks will aim to cover a wider variety of vehicle classes.



Figure I.8.1 Technologies and component parameters considered in this analysis. Their combined effect on fuel economy and cost benefit was evaluated in prior work, while this effort focuses on the individual contribution of each technology.

For Task 3, the sizing code was migrated from Autonomie Rev16 to AMBER-Autonomie, the newer version of the simulation tool. Several updates in the control and plant models were implemented as part of AMBER (which stands for 'Advanced Model Based Engineering Resource'); we quantified the impact of these changes to the vehicles used for this analysis.

As part of the review of the sizing process by industry partners, Navistar provided its vehicle performance characteristics. A more generic requirement list for trucks was proposed by the powertrain working group

under the 21CTP program. Based on this feedback, we made several changes to the sizing algorithm. The major updates were as follows.

- 1. Launch at grade: fully loaded vehicles should be able to start moving from standstill at a grade. The magnitude of the grade varies depending on the vehicle. This capability will guide the final drive and gear ratio selection.
- 2. Highway gradeability: at highway speeds, heavy trucks should be able to sustain the cruising speed at a grade. The magnitude of the grade could vary between 1%–1.5% based on the type of truck. LD vehicles were already sized to sustain cruising speeds at up to 6% grade.
- 3. In prior years, all performance tests were performed at the median weight for the vehicle weight class. All performance tests are now conducted at the maximum allowed gross vehicle weight rating (GVWR) for that particular class of vehicle.
- 4. Energy consumption tests will now be conducted with vocation-specific cargo loads. For example, the Class 8 sleeper will be sized for a test weight of 80k lb., although the fuel economy test will be performed with 38k lb. of cargo weight, based on feedback received from industry partners through 21CTP efforts.
- 5. Test duration is now specified for electric powertrains, to account for thermal de-rating of motors. Launch and acceleration tests can utilize the transient peak rating of the motor, but tests where sustained grades are encountered will account for the continuous power requirement of the electric machine.

The primary input needed for Task 4 was the technology improvement forecast for the next three decades. Although we had expected to receive this information from NREL by the end of the first quarter of FY20, it was delayed. As a result, the techno-economic analysis could not be completed during FY20. The groundwork to run these simulations is complete. We will carry out this analysis for both light- and heavy-duty vehicles as soon as we receive the inputs from NREL.

Analysis Results

Results from this year's analysis activities (following the task outline laid out in the approach section):

Task 1. Vehicle-level Assumptions

Light-duty vehicles

Cold-start penalty updates

The cold start penalty is defined as the penalty associated with different sections of the Urban Dynamometer Driving Schedule (UDDS). There are two different cold-start penalties to be applied—on Bag 1 (corresponding to fuel consumption over the first 505s of the UDDS) and Bag 2 (corresponding to fuel consumption over 506–1372 s of the UDDS). (Note that Bag 3 is for the first 505s of the second UDDS cycle with a warmed up engine. Bag 4 represents the remaining part of the cycle.)

The cold-start penalty equations that follow are derived from the bag-specific fuel economy (F.E.) values in the U.S. Environmental Protection Agency's (EPA's) test car database.

Cold start penalty on Bag 1 =
$$\frac{F.E. \text{ on Bag 3}}{F.E. \text{ on Bag 1}} - 1$$

Cold start penalty on Bag 2 = $\frac{F.E. \text{ on Bag 4}}{F.E. \text{ on Bag 2}} - 1$

In FY20, we updated the cold-start penalty assumptions based on the values observed in MY20 vehicles in the EPA test car data². Previously, we had used a single cold-start penalty value across the different engine types (naturally aspirated / turbocharged). Recent data from EPA shows that there is an influence of the different

engine aspiration methods over the cold-start penalty on Bag 1. Therefore, we decided to separate out the coldstart penalty on Bag 1 fuel economy associated with the different engine types. Similar to the Bag 1 cold-start penalty, we further evaluated the effect of the additional penalty on Bag 2

As was the case with the Bag 1 cold-start penalty, the data showed the influence of the different engine types on the additional cold-start penalty on Bag 2. Based on our detailed analysis, we determined that we will use the combinations of cold-start penalties in FY21 runs for light-duty vehicles shown in Table I.8.2.

NA / TC ^a	Bag	Penalty (%)		
NA	Bag 1	14.6		
	Bag 2	2.3		
TC	Bag 1	13.8		
	Bag 2	1.7		

Table I.8.2 Cold-Start Penalty Combinations for FY21

^a NA = naturally aspirated; TC = turbo-charged.

Engine displacements and number of cylinders

As part of our FY20 analysis, we also evaluated the different engine displacements that are available across the engines, and which vary by number of cylinders. This was done to update the relationship used in the previous analysis runs and also because this engine characteristic influences the engine costs. We further evaluated the influence of major manufacturers on engine displacements. We can use 15 different engine displacements to cover about 93.2% of the conventional engines. The different sets of engine displacements to be modeled are listed in Table I.8.3.

Table I.8.3 Engine Displacement Sets

Number and Configuration of Engine Cylinders	Engine Displacement (L)		Total
4-cylinder, in-line (I4)	NA ^a	1.5, 1.6, 1.8, 2, 2.5	6
	TC	1.4, 1.5, 2	
6-cylinder, V6	NA	3.5, 3.6, 4, 4.3	5
	TC	3	
8-cylinder, V8	NA	5.3, 5.6, 5.7, 6.2	4

^a NA = naturally aspirated; TC = turbo-charged.

Updated vehicle-level assumptions for all MD/HD vehicles are provided as part of a separate report.

Task 2. Technology-specific Contributions

The result of this task is a split of overall benefits into smaller components that can be attributed to a particular technology. The analysis considered not just the energy consumption benefits, but also the share of changes to vehicle cost. The stacked bar diagram in Figure I.8.2 shows the component-specific division of fuel and cost savings.



Figure I.8.2 The new process developed during this project quantifies the energy consumption improvements attributable to each component.

Task 3: Sizing Process

Component sizing was carried out for 25 vehicles, spanning medium and heavy duty vehicle classes and multiple vocations. Based on Vehicle Inventory and Use Survey (VIUS) data, this list will cover more than 59% of the trucks by number of models, 82% of the miles driven by U.S. trucks, and 85% of the fuel used by U.S. trucks. We will make the fuel economy, performance, and cost estimates available for all of these vehicles as part of this work. Some of the sizing results depend on component technology parameters; for example, the energy density of the battery will determine the weight of the pack and overall power requirement of the components. We currently await the necessary technology forecast information from NREL in order to finalize the sizing for future vehicles. The full set of updated MD/HD assumptions and results will be shared from Argonne website.

The sizing process ensures that the vehicles have comparable performance even when changes to the powertrains occur. This criterion is perhaps the most important for commercial trucks, as they are often designed to meet the demands of a particular use case. The payload or speed capabilities of a truck can have direct impacts on its functional utility. Therefore, the performance-based sizing should serve as the cornerstone for all of our efforts in comparing the benefits of technologies in the medium- and heavy-duty domains.



Figure I.8.3 The sizing process provides the component power and energy rating needed to meet performance targets. (Note: ISG stands for 'integrated starter generator,' and is synonymous with a "mild hybrid" that can start and stop the engine in order to order to avoid idling.)

The component sizing results for various powertrains are shown in Figure I.8.3. It is interesting to note that for this particular application, we do not expect any change in the overall propulsion power requirement even when the powertrains change. Hybrid vehicles cannot employ engine downsizing in this case, as the power needed to meet some of the performance requirements must be supplied on a continuous basis. PHEVs can have engine downsizing in this case, however, as the battery is large enough to support the engine while negotiating steep

roads. The updated sizing procedure for all vehicles was implemented in AMBER. The new sizing requirements on launch capability and the ability to sustain cruising speeds over highway grades highlighted the need for multispeed transmissions for electric drivetrains in the case of certain truck applications.



Figure I.8.4 Illustration of the shift in operating points when gear ratios and final drive ratios are changed.

Figure I.8.4 shows how the use of a transmission in a long-haul truck application enables the downsizing of the electric machine. There are three separate speed and torque requirements shown, namely, launch (at 15% grade), grade speed (at 6% grade), and cruise (at 1.25% grade). The red dots follow a constant power line, depicting the change in motor operating conditions as we search for an appropriate final drive ratio. On the plot on the left-hand side, the cruise test is a critical requirement, as the motor we chose just meets the necessary power and torque required at that speed. If we change the final drive ratio, we can reduce the cruising speed, but we will not be able to meet the torque needed by the launch test requirement. Adding a gear for cruise allows us to bring the cruising speed down, and the sizing algorithm picks a new final drive ratio and lower motor power, which will meet all of the performance requirements. This algorithm will produce results that are unique for every application, as the performance requirements differ significantly among the vehicles.

Task 4: Fuel Economy Simulations

Task 4 was expected to cover the fuel economy simulations with an updated technology forecast provided by DOE. NREL is in the process of collecting this input from various DOE offices. VTO management and the research team decided to postpone this task to ensure that the assumptions related to technology progress are consistent across the various studies being conducted by the VTO. This task will be taken up in the first quarter of FY21, after the assumptions are collected and approved by DOE.

Conclusions

All of the tasks ramping up to the large-scale simulations were completed in FY20, and Task 4 was postponed to FY21 due to delays in receiving the necessary input data. This delay has allowed the team to devote more time to testing the sizing scripts and performing a wider review of vehicle assumptions. This effort will ensure a quicker evaluation of energy consumption and cost of vehicles, as Task 4 is resumed in FY21.

As features are increasingly being automated and integrated into Autonomie as out-of-the-box functions, Argonne is able to evaluate more vehicles and drive cycles while expending the same level of effort. The process developed for this work is useful in supporting various activities, including the road map development for USDRIVE and 21CTP.

References

- 1. Autonomie [software], Argonne National Laboratory, Lemont, IL. <u>www.autonomie.net</u>, accessed October 5, 2020.
- 2. EPA (U.S. Environmental Protection Agency), 2020. Data on Cars Used for Testing Fuel Economy. Available from <u>https://www.epa.gov/compliance-and-fuel-economy-data/data-cars-used-testing-fuel-economy</u>, accessed October 5, 2020.

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I.9 Electric Vehicle (EV)-Grid Analysis Modeling (Lawrence Berkeley National Laboratory)

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Non-DOE share: \$0

Project Introduction

The transportation sector is undergoing a transformation through the introduction of on-demand mobility and vehicle automation [1]. These advances, combined with electrification, could create new synergies that would provide high-quality, low-cost, and energy-efficient mobility at scale [2]. However, the adoption of plug-in electric vehicles has been relatively slow for several reasons, including technological uncertainty, slow charging, range anxiety, and higher capital costs than other types of vehicles [3]. While there is still a great deal of uncertainty around the exact impact that automated vehicles would have on the transportation system in the coming decades [4],[5] many believe that they would 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 [6]. Each SAEV has 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 "shared" across many short periods 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 [7].

Increasing levels of renewable energy are being added to the electric grid while vehicle electrification is on the rise. The impacts of integrating 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 and emerging vehicle electrification opportunities (e.g., micro-mobility, truck electrification) using the Grid-Integrated Electric Mobility Model (GEM). This national model simultaneously optimizes the provision and operation of SAEVs to provide electrified mobility and an economic dispatch of power generation.

This project developed the GEM model to explore the dynamics and impacts of an integrated intelligent 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

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The purpose of this project was to develop new methodological capabilities that enable the simulation of future electrified and autonomous transportation systems (e.g., SAEVs) and to quantify the national impacts of electrified mobility-grid interactions. The impacts include electricity consumption and peak electricity load, charging infrastructure needs and costs, power plant operation costs in unmanaged as well as smart charging

scenarios, fleet size and vehicle range requirements, vehicle miles traveled (inclusive of estimates of demand rebound and mode shifting for passenger travel), grid infrastructure upgrades necessary to support the growing loads from transportation applications, and greenhouse gas emissions of the EV-grid systems.

Approach

The project developed an optimization model that solves for the cost-minimizing dispatch of personal EV and SAEV operation and charging, the allocation of SAEVs to serve mobility, the investment and construction of an SAEV fleet and supporting charging infrastructure, and the economic dispatch of electric power plants for US bulk electricity grid. The power sector was included by coupling GEM to the Grid Operation Optimized Dispatch (GOOD) electricity model (Jenn et al. 2020). 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 convex optimization to quadratic programming), allowing for heterogeneous vehicle ranges and charger levels. The model minimizes the total system costs (i.e., operating costs and capital costs) by choosing the timing of vehicle charging subject to the constraint that mobility demand is always served, the constraint that energy is always conserved, and the constraint that generation assets on the grid are 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.

The scope of the GEM is the contiguous US, and the mobility demands for 13 regions are explicitly modeled. In addition to developing the optimization model, the project curated a set of empirically derived inputs and assumptions for the model application (Figure I.9.1). Some of the 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.9.1 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

Results

Figure I.9.2 shows results for key outputs averaged over time (i.e., selection of days that we simulated) and geography, displayed across the full range of the fraction of mobility demand satisfied by SAEVs (S), assuming uncontrolled charging for privately-owned EVs.

Figure I.9.2 (a) shows the optimal fleet size of SAEVs and privately-owned EVs, which decreases by order of magnitude from ~145M vehicles in the S = 0% case (these 145M vehicles are "active" vehicles used on a typical weekday and represent ~56% of the current stock of US light-duty vehicles) to ~12M vehicles in the S = 100% case. This occurs because the utilization of the SAEV fleet is about 12 times higher than that of private EVs due to increased time spent moving, the number of passengers per trip, and faster recharging times. On average, across the scenarios, the cost-minimizing SAEV fleet distribution comprises 27% of vehicles with an all-electric range of 75 miles, 69% with 150 miles, and 4% with 225 miles. For comparison, the range of private EVs was a scenario assumption rather than a result of the optimization, so their distribution reflects a projection that the fleet-average vehicle range would increase steadily but modestly over time due to technology improvement and more stringent regulation.

Figure I.9.2 (b) shows the number of chargers needed. As with fleet size, there are far more chargers when SAEVs are not available (S = 0%; 195M chargers) than a counterfactual scenario of a fully SAEV fleet (S = 100%; 2.6M chargers), reflecting much higher utilization among SAEV chargers. These chargers consist of roughly half lower power levels (≤ 20 kW) and half 50 kW DC fast chargers. Additionally, about 1% of the chargers support extreme-fast charging (100 kW and 250 kW chargers).

Peak power, shown in Figure I.9.2 (c), also decreases substantially as the fraction of mobility demand met by SAEVs increases: Peak demand is 161 GW at S = 0% and is almost halved (~89 GW) when S = 100%. The dramatic increase in the SAEVs' contribution to peak power between S = 50% and 75% can be understood as follows: when S = 50%, the SAEV loads can still "valley fill" within the private EV load, whereas when S = 75% the SAEV load becomes dominant throughout the day. The peak demand increases from S = 75% to 100%. This result seems counter-intuitive, but reflects further system cost reduction opportunities through expanded charging scheduling available to a full SAEV fleet. The increase in demand charge cost is outweighed by the reduced vehicle purchase cost of private vehicles.

Like peak power, the total cost of ownership for the EV fleet decreases by 56% as the fraction of mobility demand met by SAEVs increases from 0% to 100% (Figure I.9.2 (d)). Across this range, both energy and charger costs are outsized by vehicle purchase cost. However, due to higher utilization and smaller average battery size of SAEV fleets, total vehicle cost for S = 100% is only reduced to half that of the S = 0% scenario. The smaller battery sizes of SAEVs means that the vehicles tend to charge more frequently. The decrease in total overall cost is due to the higher utilization of fleet vehicles versus private vehicles. As S increases, the relative cost per vehicle is higher as the average battery capacity is slightly larger and, the fleet turnover is faster (due to higher utilization).

Finally, Figure I.9.2 (e) shows the consequential greenhouse gas (GHG) emissions of EV fleet charging. We note that consequential impacts are more relevant because they represent the system response due to a particular factor, whereas attributional impacts allocate the total impacts to all contributing factors proportionally to their contribution (usually measured by energy consumption). Emissions fall from ~600 Mt CO_2 -eq in the case without SAEVs (S = 0%) to ~340 Mt CO_2-eq in the case of full SAEVs (S = 100%). By comparison, emissions from a gasoline-powered private vehicle fleet are 1,134 Mt CO_2-eq, including those emitted from vehicle tailpipes and during vehicle manufacturing. The GEM model does not explicitly minimize total GHG emissions (i.e., not in the objective function). Still, an overall positive correlation between operating cost and emissions for power plants leads to a reduction in fossil GHG emissions arising from greater use of controlled charging. Also, SAEVs consume less energy due to higher energy efficiency, and the vehicle manufacturing emissions are lower due to the smaller (even though more rapidly overturning) SAEV fleet. The net effects are a 43% reduction in GHG emissions between the S= 0% case and the S=100% case, or a 70% reduction in emissions from a fleet of 100% gasoline-powered private vehicles.



Figure I.9.2 Panel (a) Fleet size, (b) numbers of chargers, (c) peak power demand, (d) total cost of ownership, and (e) consequential GHG emissions vs. fraction of SAEV trips (S).

Conclusions

The configuration of a mobility system in which SAEVs serve the mobility demand has substantial benefits over one that relies on privately-owned EVs or gasoline-powered vehicles. Mobility is successfully fulfilled by a small fraction of the total number of vehicles on the road today, supported by a surprisingly small number of corresponding EV chargers. From an economic standpoint, system costs are significantly reduced through sharing and automation, while fuel and operational costs remain much lower than those of gasoline vehicles today. From an electric power grid operator's perspective, SAEVs can 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 the flexibility in charging times). Finally, the overall GHG emissions from the mobility system decrease substantially, even though GHG emissions are not explicitly modeled in the optimization model (GEM).

Key Publications

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- Szinai, Julia K, Colin J R Sheppard, Nikit Abhyankar, and Anand R Gopal (2020). "Reduced Grid Operating Costs and Renewable Energy Curtailment with Electric Vehicle Charge Management." *Energy Policy* 136: 111051. <u>https://doi.org/10.1016/j.enpol.2019.111051</u>.
- Jenn, Alan, Kyle Clark-Sutton, Michael P Gallaher, and Jeffrey Petrusa (2020). "Environmental Impacts of Extreme Fast Charging." *Environmental Research Letters* 15: 9. http://iopscience.iop.org/10.1088/1748-9326/ab9870.
- 3. Sheppard, Colin J R, Alan Jenn, Jeffery Greenblatt, Gordon Bauer, and Brian Gerke (2020). "Private versus Shared, Automated Electric Vehicles for US Personal Mobility: Energy Use, Greenhouse Gas Emissions, Grid Integration and Cost Impacts." *Environmental Science & Technology* (Under review).

4. Tong, Fan, Alan Jenn, Derek Wolfson, Corinne D Scown, and Maximilian Auffhammer (2020). "Energy, Health, and Climate Impacts from Long-Haul Truck Electrification." *Proceedings of the National Academy of Sciences of the United States of America* (Under review).

References

- Greenblatt, Jeffery B., and Susan Shaheen (2015). "Automated Vehicles, On-Demand Mobility, and Environmental Impacts." *Current Sustainable/Renewable Energy Reports* 2(3): 74–81. <u>https://doi.org/10.1007/s40518-015-0038-5</u>.
- Fulton, Lewis M. (2018). "Three Revolutions in Urban Passenger Travel." Joule 2 (4): 575–78. https://doi.org/10.1016/j.joule.2018.03.005.
- Green, Erin, Steven Skerlos, and James Winebrake (2014). "Increasing Electric Vehicle Policy Efficiency and Effectiveness by Reducing Mainstream Market Bias." *Energy Policy* 65 (0): 562–66. <u>https://doi.org/10.1016/j.enpol.2013.10.024</u>.
- Stephens, T. S., Jeff Gonder, Yuche Chen, Z. Lin, C. Liu, and D. Gohlke (2016). "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles." NREL/TP-5400-67216.National Renewable Energy Laboratory, Golden, CO. <u>https://doi.org/10.2172/1334242</u>.
- MacKenzie, Don, Zia Wadud, and Paul Leiby (2014). "A First Order Estimate of Energy Impacts of Automated Vehicles in the United States." In Transportation Research Board Annual Meeting. Vol.93.
- Chen, T. Donna, Kara M. Kockelman, and Josiah P. Hanna (2016). "Operations of a Shared, Autonomous, Electric Vehicle Fleet: Implications of Vehicle & Charging Infrastructure Decisions." *Transportation Research Part A: Policy and Practice* 94 (0): 243–54. https://doi.org/10.1016/j.tra.2016.08.020.
- Bauer, Gordon S., Jeffery B. Greenblatt, and Brian F. Gerke (2018). "Agent-Based Simulation of Automated Electric Taxi Fleets with Variable Battery Range and Charging Station Distribution." <u>https://trid.trb.org/view/1496463</u>.

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I.10 Tracking Evolution of Electric Vehicles and New Mobility Technology (Argonne National Laboratory)

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Non-DOE share: \$0

Project Introduction

Department of Energy's (DOE) Vehicle Technologies Office (VTO) invests in quality data and information, both current and historical, regarding all levels of transportation technologies to inform analysis, analysissupported activities, and associated stakeholders. VTO has supported analysis of light-duty market trends in order to assess potential benefits of VTO technologies and evaluate program activities. A major challenge is the lack of readily available historical sales and policy (both financial and non-financial) in the U.S. and other markets, and limited understanding of advanced vehicle sales trends, mobility trends and consumer choice geospatially in the U.S. Moreover, regional E-drive vehicle purchase trends and mobility usage patterns need to be systematically examined to provide support and guidance for national impacts 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 by conventional internal combustion engine vehicles, affecting oil prices and extraction (OPEC, 2018). Refineries need to know the potential impact on demand for their refining mix; gasoline and diesel are the two most common end products in the United States (DOE, 2017). Advanced vehicle technologies covered in this study include E-drive vehicles, shared mobility (e.g., ride sharing, ride hailing, etc.), and connected and automated vehicles. Electric-drive vehicle technologies include HEV, Plug-in hybrid electric vehicle (PHEV), and battery electric vehicle (BEV).

Objectives

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This project synthesizes and improves upon data for electrification and mobility technologies to evaluate the impacts of these new technologies. The project 1) summarizes public announcements for electric vehicles, new mobility, and connected and automated vehicle (CAV) technologies in the near-future, 2) collects market and usage data of new mobility technologies, such as e-bikes, e-scooters, transportation network companies (TNCs), and CAVs, 3) documents national-scale impacts of plug-in electric vehicles (PEV), 4) summarizes trends in efficiency, features, capabilities, and technologies of electric vehicles from advanced vehicle test data both in-lab and on-road, and 5) tracks Li-ion battery production by manufacturer and location for the plug-in vehicles (PEVs) sold in the U.S.

The project will provide quality data and information on electrification and new mobility technologies to the VTO Analysis Program and external researchers. Documenting the evolutionary trends and high-fidelity characteristics of these technologies could inform and facilitate numerous analyses inside and outside of DOE, examining such aspects as their energy, emission and economic impacts.

Approach

There are five tasks under this project. The following describes the method for each task separately.

Task 1. E-drive vehicle sales tracking and announcement tracking

This task collects monthly E-drive vehicle sales by maker and model from various resources, and summarize the market trends and technology evolution of E-drive vehicles in a monthly report. Argonne shares the monthly report with DOE, lab researchers and public subscribers. Argonne also publishes selected data on the following webpage: https://www.anl.gov/es/light-duty-electric-drive-vehicles-monthly-sales-updates. Sales data are compiled from several sources at different points in time.

This task also examines announcements made by automobile original equipment manufacturers (OEMs) and key suppliers on projected deployment of technologies which have the potential to impact energy usage and petroleum consumption. The focus is on the domestic, U.S. market, but worldwide announcements are included as appropriate and put into the proper context. This task tracks announcements about electric vehicles, CAV technologies, and deployment of new mobility technologies.

Task 2 New mobility technologies

This task collects market and usage data of new mobility technologies to establish an ongoing database of such data, and to uncover insights and trends from new mobility technology that present energy challenges and opportunities. Data is compiled and shared for a variety of new mobility technologies, including but not limited to e-bikes, e-scooters, TNCs, and CAVs. This data is collected at both an aggregate level (e.g., how many markets have TNC service, how many rides are being taken nationwide), and at a more detailed level where available (e.g., TNC data for the Chicago metropolitan area).

Task 3 Assessment of PEV technologies

This task conducts a national-scale evaluation of plug-in PEVs on an annual basis and summarizes the evaluation in a public-facing report. This report includes national-scale metrics such as aggregate electricity consumption and gasoline consumption reduction, and vehicle-level metrics such as average vehicle performance. This report also shows the evolution of PEV characteristics such as sales-weighted electric range and energy consumption per mile. This information is also used to inform numerous analyses inside and outside of DOE; for example, this data is used to estimate the amount of batteries available for recycling in the United States and the quantities of specific materials (e.g., cobalt). This task will also inform evaluations of regional similarities and differences within the homogeneous PEV market, specifically their regionally variable energy consumption profiles (to be completed in FY21). Historical nationwide sales data can be linked with state-by-state registration data and knowledge about OEM sales decisions (i.e., "compliance car") to assess regional impacts of electric vehicles, which will be of use when examining electricity consumption, emissions, consumer costs, and other metrics.

Task 4 High Fidelity EV Characterization

Leveraging both published EPA certification data and data collected via ANL's dynamometer facility, this task provides detailed efficiency metrics based on EPA CAFE drive cycle test results. Various aspects of efficiency (including rolling resistance, road load at 65 MPH, drive cycle energy, drive cycle powertrain efficiency, among others) are broken out separately to see how each plug-in vehicle model achieves its relative energy efficiency. FY20 work focused on finding the best EPA data source and calculating the efficiency of each plug-in vehicle model from 2011 to 2020. Vehicle models that underwent several generation changes will be highlighted by tracking the year-by-year changes in efficiency aspects and examining which refinements likely brought about those changes.

Task 5 Battery supply-chain tracking

Using the PEV sales collected through Task 1, this task summarizes the historical and future battery cell and pack production by manufacture of the PEVs sold in the U.S. This track also tracks other usage of lithium-ion

batteries in HEV and other applications such as e-bikes, scooters, energy storage, and off-road units, based on data availability.

Results

From 2011 to 2019, annual PEV sales grew from fewer than 18,000 to more than 325,000, equivalent to an average year-over-year growth rate of 44%. In 2019, PEV sales comprised 1.9% of the total national sales of new light-duty vehicles (Argonne, 2020). The monthly PEV market shares of new car sales reached about 9% in some months in 2018 and 2019. As of 2019, five models of plug-in electric vehicles have sold more than 100,000 units in the United States: Chevy Volt, Model S, Model 3, Leaf, and plug-in Prius. For the second consecutive year, the Tesla Model 3 was the top-selling PEV in 2019; more than 150,000 of these vehicles were sold in 2019. Top 10 selling models account for over 80% of the total PEV sales. Figure I.10.1 shows the cumulative PEV sales in the U.S. The darker color shows the annual sales of the top selling models while the light color shows the cumulative sales. Characteristics such as market share, sales by auto manufacturer, sales by EPA vehicle size class, sales weighted efficiency and range, etc. can be found in Argonne's monthly E-drive report.

The study estimated this reduction in gasoline consumption based on the assumptions about how each mile would have otherwise been traveled by an ICE vehicle. For each PEV, a comparable ICE in the same size class and model year was selected in order to calculate the gasoline consumption offset by using electricity. For example, a compact PEV offsets the fuel consumption of a compact ICE vehicle, rather than comparing with a fleet-wide average. The total estimated gasoline displacement by year is graphed in Figure I.10.2. In 2019, 470 million gallons of gasoline were offset by PEVs, with 70% of this total offset by BEVs. In 2019, the average on-road BEV offset 460 gallons of gasoline, and the average PHEV offset 260 gallons. Cumulatively, through 2019, PEVs have offset over 1.4 billion gallons of gasoline, 910 million gallons by BEVs and 500 million gallons by PHEVs. A report written last year (Gohlke and Zhou, 2020) documents the details of the methodology used to estimate vehicle miles traveled, weighted efficiency, and the resulting gasoline replaced.



Top selling models account for over 80% of the sales. Others include about 30 different models



Gasoline Displacement due to PEVs by Year

Figure I.10.2 Estimated gasoline displacement from ICE vehicles by LDV PEVs by year

One interesting analysis of published EPA certification data and data collected on ANL's dynamometer facility is the efficiency progression of a particular PEV model though time. Three such vehicles are shown in Figure I.10.3: the Nissan Leaf, Ford Focus EV, and Tesla Model S. The plot shows the required driving energy on the x-axis (total positive tractive energy at the wheel) and the vehicle energy usage on the y-axis (AC Wh consumed) over the federal city cycle (UDDS). Over time, OEMs added range by adding battery capacity and thereby increasing the vehicle weight. In each case shown in the figure, additional range also required higher amounts of wheel energy to propel the vehicles. However, increased powertrain efficiency can and has offset the consumption penalty of the additional weight. The trajectory of each vehicle tells a story. The Focus EV range went from 76 miles to 115 miles in 2016. From the changes in wheel energy and consumption energy, we can estimate that 10 of the 39 added range miles came from increased powertrain efficiency. The progression of the Leaf shows how some changes in range are at a similar efficiency and others come from higher efficiency gains. The Model S saw dramatic gains in efficiency from the early generations (AC induction motor) to the latest all-wheel drive version (featuring a new PM—i.e., Permanent Magnet—machine). Looking at the entire dataset, it is apparent that performance EVs can have a powertrain efficiency boost from optimizing two drive systems in an all-wheel drive configuration.

Based on PEV sales data by make and model, this study has also summarized the vehicle assembly by country and the lithium-ion battery pack and cell production by manufacturer and location. Most electric vehicles that have been sold in the United States were assembled in the United States, as shown in Figure I.10.4. 88% of BEVs and 43% of PHEVs have been assembled in the United States. Most of the remaining PEVs sold in the United States were assembled in Japan, Germany, and Mexico.

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UDDS (City) Drive Cycle - Wall Plug AC Wh vs Wheel Energy Wh

Figure I.10.3 Comparison of fuel energy (wall plug AC Wh) and wheel energy (Wh) of Focus, Leaf and Model S under UDDS city drive cycle



Figure I.10.4 Assembly location for PEVs sold in the United States through 2019

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Battery Manufacturers are supplying ~20 GWh annually to the U.S. PEV market, shown in Figure I.10.5. Panasonic and LG Chem were the largest cell suppliers to the U.S. market from 2010 to July 2020, in both total units and battery capacity. Although the total PEV sales in 2019 were down 10% from 2018, the total battery capacity sold increased due to the success of PEV models with large batteries, such as Tesla models. Battery pack production and battery cell assembly could occur in different countries or across different companies. Over 70 GWh of batteries have been deployed in the PEVs sold in the U.S. from 2010 to July 2020. Out of that 70 GWh, over 55% of the battery cells were produced in the U.S. while the corresponding figure for battery packs is about 90%. Most of the remaining battery cells and packs for the PEVs sold in the United States were assembled in Japan, Korea, Germany, Poland, Hungary, and other countries.



Figure I.10.5 Annual PEV sales and battery capacity by battery manufacturer

Conclusions

PEV sales have been increasing in the U.S. since they were first introduced in December, 2010. More than 1.6 million PEVs have been sold in the United States since 2010. Over 325,000 plug-in electric vehicles were sold in the United States in 2019, a 10% decrease from 2018. Over 74% of annual PEV sales were BEV in 2018. PEVs account for about 2% of all light duty vehicle sales monthly.

Cumulatively, all PEVs sold in the U.S. have been driven nearly 38 billion miles on electricity. These 38 billion eVMT consumed more than 12.5 terawatt-hours of electricity while reducing gasoline consumption nationwide by 1.4 billion gallons. On average, electric vehicles have become more fuel efficient and have demonstrated increased all-electric driving ranges as technology has advanced. This improvement in efficiency has occurred even while performance metrics (such as vehicle power or acceleration) have improved as well. Most of the PEVs on the road were assembled in the United States. The market has begun to grow beyond the midsize and compact cars which were most common in the early years, with plug-in electric SUVs becoming more popular as models become available.

Most electric vehicles that have been sold in the United States were assembled in the United States, as shown in Figure I.10.4. 88% of BEVs and 43% of PHEVs have been assembled in the United States. Battery manufacturers are supplying ~20 GWh annually for the U.S. PEV market. Panasonic and LG Chem were the largest cell suppliers to the U.S. market from 2010 to July 2020, in both total units and battery capacity. Over 70 GWh of battery capacity has been deployed in the PEVs sold in the U.S. from 2010 to July 2020. Out of that 70 GWh, over 55% of the battery cells were produced in the U.S. while the corresponding figure for battery packs is about 90%.

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-20/4.

2. Argonne Light Duty Electric Drive Vehicles Monthly Sales Updates, https://www.anl.gov/es/lightduty-electric-drive-vehicles-monthly-sales-updates

References

- EEI (Edison Electric Institute), 2017. Plug-in Electric Vehicle Sales Forecast Through 2025 and the Charging Infrastructure Required. Prepared by Adam Cooper and Kellen Schefter, June 2017. <u>http://www.edisonfoundation.net/iei/publications/Documents/IEI_EEI%20PEV%20Sales%20and%20</u> <u>Infrastructure%20thru%202025_FINAL%20%282%29.pdf</u>
- DOE (U.S. Department of Energy), 2017. Motor Gasoline Is Most Common Petroleum Product from U.S. Refineries. February 13, 2017. <u>https://energy.gov/eere/vehicles/fact-964-february-13-2017-</u> motor-gasoline-most-common-petroleum-product-us-refineries
- DOE and EPA (U.S. Department of Energy and Environmental Protection Agency), 2019. FuelEconomy.gov. Accessed January 22, 2019. <u>http://fueleconomy.gov/</u>
- 4. Gohlke, David and Yan Zhou, 2019. Impacts of Electrification of Light-Duty Vehicles in the United States, 2010–2019. Report ANL/ESD-20/4, DOI: 10.2172/1642114.
- NHTSA (National Highway Traffic Safety Administration), 2018. Part 583 American Automobile Labeling Act Reports. Accessed December 3, 2018. <u>https://www.nhtsa.gov/part-583-american-automobile-labeling-act-reports</u>
- OPEC (Organization of the Petroleum Exporting Countries), 2018. 2018 OPEC World Oil Outlook 2040. ISBN 978-3-9503936-6-8. September 2018. <u>https://woo.opec.org/</u>
- 7. SEPA (Smart Electric Power Alliance), 2017. Utilities and Electric Vehicles: The Case for Managed Charging. <u>https://sepapower.org/resource/ev-managed-charging/</u>
- 8. Argonne Light Duty Electric Drive Vehicles Monthly Sales Updates, <u>https://www.anl.gov/es/light-</u> <u>duty-electric-drive-vehicles-monthly-sales-updates</u>, accessed 10/16/2020

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I.11 Assessing Vehicle Technologies Office Benefits in a Transportation Energy Ecosystem

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Non-DOE Share: \$0

Project Introduction

The benefits of advanced vehicle technologies are traditionally assessed using standardized drive cycles. Those cycles aim to represent average driving conditions and, as such, cannot take into consideration the variety of vehicle usage that is found in the real world. In particular, current standardized drive cycles do not take into consideration the impact of connectivity and automation, including the impact that automation can have on a person's willingness to drive. In this project, all drive cycles within a geographical area were generated and used to assess the benefits of advanced vehicle technologies. Different scenarios, which included the impact of technology on passengers' traveling decisions, were considered.

Objectives

The primary objective was to quantify the potential benefits of VTO technologies at the transportation system level on a wide range of metrics, including energy, cost, greenhouse gases (GHG), and mobility, and compare them with U.S. standard drive cycles. The transportation system network in this project is the Chicago metropolitan area. The broad-scale setting will allow quantifying the technology impact in a wide range of real world conditions and studying the sensitivity to selected parameters (fuel and electricity cost, value of travel time on mode choice and miles traveled).

Approach

The project involves Argonne National Laboratory, Oakridge National Laboratory and the National Renewable Energy Laboratory. The interactions between the laboratories were coordinated through a workflow that defines how information flows between the different tools developed by the laboratories. POLARIS [1] models the transportation network and generates trip information for all agents within the network. SVTRIP [2] and Autonomie [3] are used to determine energy consumption for each trip. MA3T [4] provides fleet distribution information, and EVI-Pro [5] determines the number of required charging stations to support the level of electrification that is assumed in each scenario (Figure I.11.1). A variety of outputs can be calculated for each scenario, including energy consumption, mobility energy productivity (MEP), and total cost of ownership (TCO).

Scenario definition

This study relies on scenarios defined in the DOE SMART initiative. The scenarios consider not only developments in vehicle technologies but also broader changes in transportation and communication technologies, including automation, shared mobility, e-commerce, telecommuting and other trends that have the potential to have a significant impact on transportation energy consumption. More details about the scenarios can be found in the *Modeling Workflow Development, Implementation, and Results Capstone Report* [6].

Fleet distribution

Both vehicle technology and fleet distribution impact overall energy consumption. As we assessed energy consumption across scenarios, we kept vehicle technology as defined in SMART and considered 2 different fleet distributions.

Lowest-TCO distribution

For each scenario, we ran all vehicles with five powertrains: conventional, belt-integrated starter generator (BISG, mild hybrid 48V), hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), and battery electric vehicle (BEV). Vehicle class was not changed. For example, for a household in Chicago that owns a midsize car, we estimated five energy consumptions for that household using a midsize car and five powertrain options. We then calculated the TCO for each powertrain option. While a passenger car buying decision is a complex decision and goes beyond the scope of this project, the intent is to determine what the powertrain distribution would look like if the buying decision were solely based on TCO.

TCO assumptions

The following are the main assumptions used in the TCO calculation:

- Electricity, gasoline and diesel cost are derived from the 2019 IEA Energy Outlook.
- Yearly vehicle miles of travel (VMT) is calculated by scaling up daily VMT so that, on average, vehicles drive 14,000 miles per year. The distribution includes vehicles that have very high yearly mileage and very low yearly mileage.
- TCO is expressed in \$/mile and includes the purchase price of the vehicle (manufacturer's suggested retail price or MSRP) as well as the discounted energy cost over 12 years.
- A 4% discount rate is used for the energy cost calculation.
- Other costs, such as insurance and maintenance, are not taken into account.

MA3T VTO Benefit Analysis distribution

The vehicle distribution from MA3T used in the VTO Benefit Analysis was implemented in POLARIS, and energy consumption was estimated. Only baseline scenarios were considered, as the VTO Benefit Analysis does not consider connectivity and automation. Using the same distributions, we can then compare energy consumption using Vision [7] (which uses distributions from MA3T and energy consumption from regulatory cycles) and POLARIS. As vehicle types and assumptions do not match perfectly between the different tools, adjustments were made to make the comparison as realistic as possible. For example, Vision uses stock fleet representation, while POLARIS uses sales distribution. Vision files were modified to use sales as inputs rather than stock.

Results

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Lowest-TCO distribution

When the powertrain that provides the lowest TCO is selected for each vehicle in the distribution, the percentage of electrified vehicles increases when compared to the original SMART distribution. Figure I.11.1 highlights the results for privately owned vehicles (single-occupancy vehicles or SOVs). In the Base Today scenario, 20% of the powertrains that provide the lowest TCO are HEV. For short-term (ST) scenarios, BEVs account for approximately 15% of the lowest-TCO powertrains, while the penetration is estimated at around 1% in the SMART scenarios. For long-term (LT) scenarios, the penetration of BEVs providing the lowest TCO is generally in line with the SMART assumptions. PHEV powertrains are also more common in long-term scenarios when considering TCO. BISG powertrains almost never provide the lowest TCO, particularly for long-term scenarios.

Figure I.11.2 shows the lowest-TCO powertrain distribution for transportation network company (TNC) vehicles. The penetration of highly electrified powertrains is significantly higher than in the SOV category. The penetration of conventional powertrains is below 20%. PHEV and BEV make up almost all powertrains in long-term scenarios. The difference in powertrain penetration between TNCs and SOVs is primarily driven by the higher VMT incurred by TNC. As VMT increases, the penetration of electrified vehicle increases as it gets easier to balance out the higher purchase price with the lower driving cost.



Lowest TCO distribution - SOV



Figure I.11.1 Lowest-TCO and SMART powertrain distribution



Lowest TCO distribution - TNC

Figure I.11.2 Lowest-TCO powertrain distribution for TNC

Figure I.11.3 shows how TCO changes as a function of VMT for two selected scenarios. First, it highlights that TCO is primarily dependent on VMT, and that for a given VMT, the difference in TCO between different



powertrains tends to be very small. Second, it takes 35,000 miles or more for a BEV or PHEV powertrain to provide the lowest TCO in the Base Today scenario. That number drops to 9,000 miles in scenario C-high.

Figure I.11.3 TCO as a function of VMT for selected scenarios

MA3T VTO Benefit Analysis distribution

Based on MA3T sales distribution, new vehicle fleets are defined and used as input to POLARIS runs. The baseline scenarios (Base Today, base ST-low, base ST-high, base LT-low, and base LT-high) are evaluated with the new fleets. MA3T fleets do not consider BISG separately and include fuel cells (FC) as a powertrain option.

The improvements in kWh/mile in the different scenarios are almost identical in the POLARIS simulations and the VTO Benefit Analysis. However, the decrease in total energy consumption for long-term scenarios is smaller for the VTO Benefit Analysis. The difference is explained by the VMT progression between scenarios (Figure I.11.4). For the city of Chicago, Polaris relies on the Chicago Metropolitan Agency for Planning (CMAP) for land use, population growth, and VMT increase. VMT is expected to increase by approximately 10% in long-term scenarios. The VTO Benefit Analysis uses assumptions from the 2019 *Annual Energy Outlook* and reflects changes at the national level. A primary driver for the 30% increase in VMT at the national level in long-term scenarios is driven by an increase in the driving age population.


Figure I.11.4 VMT progression for POLARIS simulations and VTO Benefit Analysis

MEP results for TCO and MA3T runs

A new set of energy and cost value parameters was provided from TCO and MA3T runs as input to the MEP calculation procedure. It is important to note here that the network state (i.e., travel times) for all runs is the same as the respective SMART 1.0 runs. As expected, MEP for every TCO scenario is higher than that of the corresponding SMART scenario, reflecting the higher level of electrification (Figure I.11.5).



Figure I.11.5 MEP score comparisons between SMART and TCO runs

Charging stations

In this analysis two approaches are used for generating BEV fleet size scenarios based on 1) a total cost of ownership (TCO) analysis conducted by ANL and 2) consumer choice modeling using ORNL's MA3T model. Significant growth in BEV fleet size results from both approaches (note that as of 2018, there were approximately 11,000 BEVs registered in the Chicago urbanized area per IHS Markit). Interestingly, both approaches find a relatively minimal impact of VTO technology targets on BEV fleet size in Chicago.

EVI-Pro translated the simulated charging demand from POLARIS into a supply of infrastructure necessary to satisfy said demand. In general, we find that as demand increases across scenarios, EVI-Pro simulates the need for more public charging stations, larger stations (in terms of number of plugs per station), and busier stations. Figure I.11.6 shows the relationship between aggregate charging demand and the average number of daily charging events per plug. We can see that in the highest demand scenarios, utilization of fast charge stations plateaus at just under 7 daily events per plug. Recall that meeting all VTO tech targets on time generally results in smaller BEV fleets, and subsequently, less demand for public charging (assuming the TCO and MA3T approaches).



Figure I.11.6 Aggregate charging demand and average daily charging events

Conclusions

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Powertrain distributions based on TCO include a higher percentage of electric (xEV) vehicles than the initial SMART scenarios. The share of electrified powertrains increases in the short- and long-term scenarios. VMT is a primary driver of TCO, and vehicles with higher VMT are more likely to be electrified, as the lower cost of energy balances out the higher purchase price. The case for electrification is higher for TNCs, which have higher VMT than SOVs. PHEV and HEV represent the major share of powertrains for TNCs.

All technologies improve over time (both on efficiency and cost). The winning powertrain from a TCO standpoint is the one that improves the most for a particular vehicle and duty cycle. PHEVs capture a significant share of powertrain distribution, as they benefit from a low energy cost, relying primarily on electricity for driving, and a relatively low purchase price, as the battery size remains significantly smaller, hence cheaper, than that of a BEV. BISGs performed poorly in the analysis and do not represent a significant share of powertrains based on TCO. Conventional powertrains still provide the lowest TCO in long-term scenarios for vehicles with low VMT.

The purchase price represents the biggest contribution to TCO for SOVs and TNCs, although the contribution is higher for SOVs. However, TCO is also highly dependent on VMT. In long-term scenarios, it will take less than 10,000 miles per year for a BEV to be on par with a conventional powertrain. It is also important to note that for a given VMT, the difference in TCO values between powertrains tends to be small. In other words, small changes in the cost and efficiency assumptions could lead to significant changes in the lowest-TCO powertrain distribution.

The determination of the lowest-TCO powertrain candidate is calculated individually for each vehicle, based on a specific duty cycle. Results from the lowest-TCO calculation are then aggregated at the geographical zone level to develop powertrain distributions that are then fed as inputs into POLARIS. The assignment of powertrains at the zone level is done with some level of randomness and before a duty cycle is determined for each vehicle. The vehicle assignment is an input to POLARIS, while the determination of the lowest TCO is based on what the vehicle actually does (VMT in particular), which is an output of POLARIS. As a result, the MEP calculation, which uses the output from POLARIS, was not entirely representative of a lowest-TCO scenario. The MEP impact is primarily due to the higher level of electrification that is obtained with the lowest-TCO powertrain distribution.

Using MA3T distributions rather than the original SMART distributions as inputs to POLARIS and comparing VTO Benefit Analysis results to POLARIS results leads to similar vehicle technology improvement (considering VTO versus BAU) from a kWh/mile standpoint. However, the expected reduction in total energy consumption in future scenarios is lower in the VTO Benefit Analysis than in the POLARIS-based analysis. The difference is primarily driven by differences between the two approaches for VMT in future scenarios: VTO Benefit Analysis assumes VMT increases of approximately 30% in long-term scenarios, while POLARIS assumes 10%.

Using POLARIS-based energy consumption rather than energy consumption based on standardized drive cycles as inputs to MA3T leads to only small changes in powertrain distributions. The current workflow of information between the different labs and tools assumes a closed loop in which outputs from one tool feed into another. The workflow could be simplified by taking market penetration out of the closed loop since the impact on powertrain distribution is low.

References

- 1. Argonne National Laboratory. Polaris (software). <u>https://www.anl.gov/es/polaris-transportation-system-simulation-tool</u>
- 2. Argonne National Laboratory. SVTRIP (software). https://vms.es.anl.gov/SVTrip/
- 3. Argonne National Laboratory. Autonomie (software). https://www.autonomie.net
- 4. Oakridge National Laboratory. MA3T (software). https://teem.ornl.gov/ma3t.shtml
- 5. National Renewable Energy Laboratory. EVI-Pro (software). https://afdc.energy.gov/evi-pro-lite
- SMART Mobility: Modeling Workflow Development, Implementation, and Results Capstone Report, U.S. DOE, July 2020, <u>https://www.energy.gov/sites/prod/files/2020/08/f77/SMART-</u> <u>Workflow Capstone 07.28.20.pdf</u>
- 7. Argonne National Laboratory. VISION (software). https://www.anl.gov/es/vision-model

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I.12 Distributions of Real-world Vehicle Travel

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Project Introduction

A vehicle mileage schedule represents the estimated annual miles driven by a typical vehicle each year as the vehicle ages. These schedules are 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 often used for these calculations. Published travel schedules typically disaggregate 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.

Furthermore, driving behavior is not homogenous, and using a single mileage schedule for all calculations related to lifecycle emissions, cost of ownership, and vehicle survivability does not yield a full understanding of fleet-wide fuel consumption. Optimal vehicle choices from a levelized cost of driving standpoint may vary depending on differing use cases. New technologies are more likely to be useful to a subset of consumers before the whole market, e.g., a battery electric vehicle driven more intensively than the average may have an easier time reaching cost parity than a "typical" vehicle. Detailed understanding of vehicle travel at a disaggregated level is necessary to quantify important metrics more accurately.

Objectives

This project aims to understand what key metrics are changed by variations in light-duty vehicle usage, and how. In particular, this project 1) quantifies variations in vehicle miles traveled (VMT), considering vintage, vehicle characteristics, and demographic characteristics; 2) quantifies levelized cost of driving (LCOD) for vehicles with different use intensities; 3) estimates how variations in VMT impact national-scale metrics such as fuel consumption and emissions, both for today's vehicles and potential future scenarios; and 4) assesses variations in vehicle survivability. These results will be broadly shared to better inform calculations by DOE and others.

Approach

This project uses light-duty vehicle data from the National Household Travel Survey (NHTS) and state odometer readings to explore the nationwide distribution of vehicle miles traveled (VMT). This distribution has been examined as a function of multiple parameters related to the vehicle age, vehicle characteristics, and demographics. The data derived from the NHTS datasets is compared with historical data published by the U.S. Department of Transportation (DOT) and the U.S. Environmental Protection Agency (EPA) both for validation and to analyze changes in how vehicles have been used over time.

In this project, levelized cost of driving (LCOD) is the metric used to assess costs of different vehicle technologies for different driving habits. LCOD calculations will focus on vehicle purchase costs and fuel costs, and include other costs (such as vehicle maintenance and repair), data-permitting. In particular, this

project analyzes cost-competitiveness of different technologies for low-, medium-, and high-intensity driving. For higher VMT, fuel costs will be a larger portion of the total cost. For a given set of vehicle technologies, LCOD is calculated to find the tipping point where technology A becomes cost-competitive with technology B. This will be combined with VMT distribution data to find what fraction of potential drivers would be better suited with advanced vehicles, using currently-available vehicles (i.e., model year 2020 vehicles) and simulated vehicle data for future vehicles, derived from Argonne's Autonomie model, to quantify the LCOD.

This project will also examine how vehicle survivability and scrappage rates vary across the light-duty fleet. Fleet turnover will impact how quickly new technologies enter the passenger vehicle market. Historical sales data is compared with vehicle registration data and household vehicle data to analyze vehicle survivability for different size classes, powertrains, and fuel efficiency, pending data availability. Per-vehicle VMT and scrappage rates will be correlated with other variables to find how VMT and scrappage are linked.

Results

Relying on data from the NHTS [1], this project has found broad ranges in how vehicles are used. Figure I.12.1 shows annual mileage as a function of vehicle age, for different percentiles ranging from the 5th percentile to the 95th percentile. While the median VMT is approximately 11,300 miles for a new vehicle, five percent of new vehicles are driven less than 2,200 miles, and another five percent are driven more than 30,000 miles. This tenfold disparity continues throughout the life of these vehicles, resulting in a large range of total travel in the vehicle lifetime.



Distribution of Annual Vehicle Miles Traveled, 5th - 95th percentiles

Figure I.12.1 Distribution of Annual Miles Traveled by Light-Duty Vehicles

Figure I.12.1 shows the variation in driving patterns across all vehicle types, but this data can be further disaggregated. Figure I.12.2 shows the related distributions for cars and for light trucks (including pickup trucks, utility vehicles, and vans). Both cars and light trucks show similar shapes, with VMT decreasing as the vehicle ages, with similar shapes across all percentiles. However, light trucks are consistently driven further

than cars through year 18, at which point the two distributions are nearly indistinguishable. This observation is consistent with previous work from the DOT and EPA [2],[3].



Distributions of VMT for Cars and Light Trucks

Figure I.12.2 Distribution of Annual Miles Traveled by Cars and Light Trucks

Beyond the vehicle size classes, vehicle technology may also impact VMT. Due to low sales shares of alternative-fuel vehicles in the United States, the NHTS does not have sufficient sample size to compare alternative-fuel vehicle mileage schedules to any great extent, except for hybrid electric vehicles (HEVs). Figure I.12.3 shows the VMT schedule for hybrid cars and non-hybrid cars. NHTS classifies only 5,447 as hybrid cars in their database, so the data is sparse (and therefore noisy). Interestingly, the hybrid cars do not exhibit the same characteristic declining shape in VMT as a function of age, instead maintaining a nearly flat VMT distribution at most percentiles for the first decade of use.



Figure I.12.3 Distribution of Annual Miles Traveled by Hybrid Cars and Non-Hybrid Cars

Demographic characteristics also greatly affect these travel distributions. Figure I.12.4 shows how driving patterns differ between urban and rural households. These figures show that driving is higher in rural areas than in urban areas, and that this is true at all percentiles. The rural distribution shows a much wider spread

between the 1st and 3rd quartiles than the urban distribution; in other words, the difference between the 75th and 25th percentiles is much larger for the rural distribution.



Figure I.12.4 Distribution of Annual Miles Traveled, Urban vs. Rural Households

To estimate scrappage, we have begun a comparison of historical sales data and registration data by make and model. Sales data for each make and model and registration data from IHS Markit [4] were all combined side by side, directly comparing the number of models sold in year x and the number of model year x vehicles that were registered within their respective states in 2017. For each vehicle make and model, the survivability was modeled using a logistic function, popular for population dynamics, following Greene and Chen [5]. The logistic function applied was:

Survivability =
$$1 - (1 + e^{-\beta ((2017 - x) - t_0)})^{-1}$$

where β represents a rate parameter, t_0 is a variable to represent the median lifetime of a model, and x represents the model year. The logistic function is solved for t_0 and β by a least squares fit between the logistic function and the implicit survivability. The implicit survivability represents how many vehicles are still in service; for a given vehicle and vintage it is found by dividing the number of registrations in 2017 by its initial sales. Figure I.12.5 shows a typical S-curve function for the implicit survivability of the Honda Civic. Additional analysis is necessary to find how the shape of this curve changes across many vehicle characteristics, such as vehicle size, fuel economy, and price.



Vehicle Survivability (Honda Civic; 2017 registrations)

Figure I.12.5 Implicit survivability for Honda Civic, for model years between 1973 and 2017.

A deeper understanding of vehicle behavior can be used to quantify economic metrics. As a simplified example, a per-mile levelized cost of driving (LCOD) can be calculated as the sum of upfront vehicle expenditures, amortized over the life of the vehicle, and ongoing fuel expenditures. Assuming that both fuel efficiency and fuel price remain constant throughout the analysis window, this becomes:

$$Total \ expenditures = Vehicle \ cost + GPM \times \left(\frac{\$}{gallon}\right) \times \sum_{i=1}^{n} \frac{VMT_{i}}{(1+d)^{i}}$$

where *i* represents the time window in which VMT_i is driven, *n* is the total length of time considered, and *d* is the discount rate. In general, these are measured on an annual basis. In this equation, the miles are "discounted", as a mathematical tool to represent the fact that a future discounted per-mile cost should have the same marginal value, independent of discount rate. Using this representation, the entirety of the VMT schedule can be represented as a single value, α , given a discount rate *d* and a total analysis window *n*. The above equation can thus be reframed as

$$LCOD = \frac{Vehicle \ cost}{\alpha \times Total \ VMT} + \frac{Fuel \ price}{Fuel \ economy}$$

This representation makes it easy to compare changes in vehicle costs with different economic or operational assumptions. For example, if discount rates are ignored, then α =1.0, and the particulars of the mileage schedule do not matter, other than the total VMT. However, with larger discount rates, the economic impact of considering the mileage schedule becomes more important. Using recent mileage schedules from the EPA [2], a 7% discount rate gives α =0.49, but if the car were driven twice as intensively with the same lifetime VMT, α =0.68, equivalent to driving 37% more total miles in terms of LCOD. This particular case is of note when considering the operation of fleet vehicles and hypothetical robo-taxis.

To determine if a novel technology (with defined upfront and recurrent costs) is cost competitive for a specific driving behavior, LCOD can be compared to find the regimes of α and total VMT where the novel technology is cost competitive. A larger discount rate is disadvantageous to technologies which have lower operating costs but higher upfront purchase costs, while higher VMT favors more fuel efficient vehicles.

Conclusions

This project has found broad distributions in vehicle travel that are highly dependent on both household and vehicle characteristics. These distributions show that a one-size-fits-all approach to LCOD is not sufficient given differences in household travel behavior, as most vehicles drive much more or much less than the "average" vehicle. (Data from this task has been used to inform inputs for a Total Cost of Ownership, or TCO, analysis in parallel DOE-sponsored research.) As described above, vehicle lifetime and typical annual travel are key input assumptions that impact TCO and LCOD calculations.

Further exploration is necessary to link vehicle travel, vehicle survivability, and operational costs together. In work planned for FY2021, this project will better understand the attributes correlated with vehicle survivability, and compare how these link with vehicle energy consumption. At a national level, this project will use the VISION model to estimate total quantities of fuel consumption given the distributions of driving. Using data on today's fleet will serve to quantify the sensitivity of aggregated results (e.g., total national fuel consumption, average carbon emissions, levelized cost of driving) to using distributions of vehicle miles rather than point estimates.

References

- 1. Oak Ridge National Laboratory, 2020. National Household Travel Survey. https://nhts.ornl.gov/
- Lu, S, 2006. Vehicle Survivability and Travel Mileage Schedules. NHTSA Technical Report DOT HS 809 952. January 2006. <u>https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809952</u>
- U.S. EPA, 2016. Draft Technical Assessment Report: Midterm Evaluation of Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards for Model Years 2022-2025. EPA-420-D-16-900, July 2016. <u>https://www.epa.gov/regulations-emissions-vehicles-and-engines/midterm-evaluation-light-duty-vehicle-greenhouse-gas</u>
- 4. IHS Markit, 2020. Vehicles in Operation (VIO) & Vehicle Registration Data Analysis. https://ihsmarkit.com/products/automotive-market-data-analysis.html
- Greene, D., Chen, C., 1981. "Scrappage and Survival Rates of Passenger Cars and Light Trucks." Transportation Research Part A, 15(5), 383–389.

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I.13 ParaChoice Model

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	determined annually	
Project Funding: \$200,000	DOE share: \$200,000	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 the affordability of transportation, while encouraging innovation and reducing dependence on petroleum. Analysis with ParaChoice enables exploration of the key factors that influence consumer choice, as well as estimation of the effects of technology, fuel, and infrastructure development on a future vehicle fleet mix. Due to distinct differences in requirements, needs, and use patterns between light-duty vehicles (LDVs) and heavy-duty vehicles (HDVs), analysis of the dynamics of vehicle adoption evolution requires separate models for each. This project, and similar vehicle choice models, have historically chosen to forgo analysis of shared technology and infrastructure between the segments in favor of capturing these distinctions. This year, the LDV and HDV ParaChoice models were integrated along shared infrastructure and fuel pathways, with potential vehicular technology spillovers considered, to more fully capture the complex nature of on-road vehicle adoption dynamics.

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 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, the input data and assumptions.

Goals of the integrated LDV-HDV analysis are as follows:

- Investigate the effects of shared infrastructure and technology spillover on the projected adoption of alternative fuel LD and HD vehicles.
- Leverage existing endogenous capabilities in ParaChoice, connecting the two models first through shared infrastructure to capture the dynamic effects of supply and demand for energy, fuels and infrastructure.
- Secondarily, provide a first-order estimate of the potential effects of technology spillover between the two segments on adoption through estimation of technology maturation and cost reduction effects.

Approach

The segment independent ParaChoice framework is a system dynamics model incorporating energy sources, fuels, and LDVs or HDVs (Figure I.13.1). Simulations begin with today's energy and fuel characteristics (e.g., prices, demand, etc.) and vehicle stock and project out to 2050. At each time step, vehicles compete for share of sales in the 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 [1],[2].



Figure I.13.1 Schematic of ParaChoice systems dynamics 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 was updated in FY20 with the recognition that the segments do not exist in isolation, but rather interact on multiple levels, including shared infrastructure, fuel and energy demand, and (potentially) technology spillover (Figure I.13.2). Shared fuel, energy source and infrastructure production models bundled demand from both light and heavy-duty segments, thus capturing the effects of capacity limits and the cost to build new infrastructure, along with the benefits of economies of scale and penalties from supply/demand mismatch. Combinations of one of each of the three; fuel type (e.g., diesel vs. hydrogen), energy source type (e.g., coal vs. biomass), and infrastructure type (e.g., gas station vs. electric chargers) are defined as appropriate to the relevant vehicle powertrains and fuels production pathways.



Figure I.13.2 Updated ParaChoice functionality where LD and HD models are integrated. At the foundation the integration occurs through fuel and infrastructure demand. Technology spillovers are an optional feature to explore the effects on adoption.

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.13.3. Baseline inputs into the ParaChoice model include the following data and modeling sources:

- GREET 2016 [3]: emissions & fuel cost
- National Household Travel Survey [4]: LDV fleet segmentation
- Polk [5]: HDV fleet segmentation and price projections
- Autonomie Vehicle System Simulation Tool 2019 [6]: fuel efficiency, electric driving range, price projections
- Alternative Fuels Data Center [7]: 2010–2017 fueling stations and policies by state
- Vehicle Inventory and Use Survey [8]: vehicle ton-mile travelled (VTMT)
- Public Transportation Fact Book [9]: VTMT
- Freight Analysis Framework V4 [10]: VTMT
- Advancing Technology for America's Transportation Future [11]: efficiency
- Final Rule for Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles – Phase 2 [12]: efficiency
- Annual Energy Outlook [13]: fuel costs
- Hydrogen Delivery Scenario Analysis Model [14]: fuel costs
- H₂A [15]: fuel costs
- Foothill Transit Agency [16]: price projections
- International Council on Clean Transportation [17]: price projections



Figure I.13.3 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)

As shown in Figure I.13.3, the ParaChoice model simplifies the available fueling infrastructure for on road travel into three primary bins: private, public truck stop, and public gas station. Under this structure the infrastructure options are further segmented into relevant factors such as fuel type and population density. The truck stop and gas station designators are used to differentiate station availability and fueling rates, reflecting realistic observations, e.g., that there are more diesel dispensers in truck stops than in gas stations, and that volumetric pumping rates for liquid fuels are higher in truck stops than in gas stations. (Truck stops and gas stations are treated as shared infrastructure in the integrated model.)

The endogenous fuel and energy pathway modeling in ParaChoice captures the supply and demand effects of a simultaneous build-out of fueling infrastructure and expansion of available powertrains. Within ParaChoice, demand is tied to infrastructure build-out and infrastructure cost so there will be a non-linear relationship among increased demand, increased cost for infrastructure build-out and reduced penalties for accessibility inconvenience as new stations are brought online.

A driving hypothesis of this work is that there would be technology spillover between LDV and HDV segments due to shared technology and simultaneous development. In some cases, certain parts of the powertrain will be common for a variety of vehicles [18],[19]. Thus the development of those technologies and the associated reduction in costs will be shared over multiple segments. One way to capture cost reduction as a result of experience is the learning curve [20],[21],[22]. In a learning curve model, each doubling of cumulative production reduces the cumulative average cost (or time) of production by a certain percentage. Common progress ratios in energy (i.e., cost reduction for each doubling) range from -34% to 50% [23], where a negative value indicates increasing prices. *Eq. 2* is Wright's cumulative average model where: *Y* is the cumulative average cost per unit, *X* is the cumulative number of units produced, *a* is the cost required to produce the first unit, and *b* is the log of the learning rate/log of 2. For our application k, j denotes vehicle segments (k \neq j).

For this effort two major components of alternative fuel vehicles (AFVs) are assumed to be candidates for learning curve cost reductions: batteries and fuel cell packs, both based on their novelty and potential to be shared between manufacturers and across applications. (Electric machines are also a probable and reasonable candidate for spillover but represent a small portion of the overall vehicle purchase cost.) Using the parametrized nature of ParaChoice can then bound the potential effects of learning curve spillover for these technologies. A learning rate of 95% means that the cumulative average cost of a product reduces by 5% for every doubling of production.

$$Y_k = a_k X_i^{b_k} \qquad Eq. \ l$$

In the isolated ParaChoice implementation, values for technology costs are pulled from the Autonomie tool [24],[25] at a given year. The progress of the technology (battery packs or fuel cell packs) is assumed to be measured in cost, with this segment well *captured* by Autonomie. All spillover effects are treated as modifiers on the Autonomie baseline. Eq. 3 is used to capture the effect of spillover year to year. Where i is the year of interest. Because spillovers are unlikely to be immediately realized a delay time in learning absorption is parametrized to interrogate how a delay effect changes the bounded results. Eq. 4 gives the adjusted cost of a vehicle in a given year accounting for spillover effects. This method applies only to the cost of batteries and fuel cells instead of the entire vehicle manufacturing cost.

$$\mu_k = \frac{Y_{i,k} - Y_{i-1,k}}{Y_{i-1,k}} \qquad Eq. 2$$

$$C = (1 + \mu)C_{Autonomie}$$
 Eq. 3

In order to base the selection of spillover delay parameters on a physically observed phenomenon, a regression analysis of reported revenues of top LDV (Toyota, Volkswagen, Ford, Honda, Hyundai) and HDV (Daimler, VW-Traton, Volvo, Paccar, Navistar) manufacturers over a 16 year period was performed. The year-to-year (YTY) change in the revenue figures was quantified and correlations between the LD and HD segments were established. (I.e., does the change in revenue in one segment manifest in the other after a certain delay period?) By sweeping across a range of delay periods, it was possible to calculate the coefficient of determination (r²) of a linear regression between LD and HD, with a YTY change. Using these observations, a 2-yr spillover delay for HD, and a 4-yr spillover delay for LD showed the highest r² and were chosen as inputs for ParaChoice. Note that this approach was intended only to provide a starting value for the spillover delay in ParaChoice, rather than to provide definitive insights into how LD and HD segments interact with each other. This interaction is a complex economic issue beyond the scope of this work, but can be targeted for future work.

Results

In fiscal year (FY) 2020, the project integrated the independent LD and HD models through shared infrastructure and developed a simplified model of technology spillover between the two segments. Results from this work will be presented at the 2021 meeting of TRB and in a research paper currently in preparation.

The intent this year was to begin resolving the issue of siloed segments in vehicle choice modeling. It is challenging to find appropriate data to validate against so, as a first measure, the results of the integrated models were compared to the independently run versions: first with infrastructure integration alone, and then to the combination of infrastructure integration and technology spillover.

While captured by the model, the effects on adoption in the LDV market are negligible. This is primarily caused by a lower contribution of infrastructure to the overall generalized cost compared to the contribution of the vehicle purchase cost.

Heavy Duty Results

Figure I.13.4 shows how the fleet fraction evolves out to 2050 for the HD fleet in uncoupled and LD infrastructure coupled simulations. There is a significant increase in the adoption of PEVs due to coupling. The increase in adoption can be attributed to the decrease in infrastructure costs, which is significant in the baseline case for HDV due to high power demands. It is worth noting that the increase in PEV adoption comes at the expense of not only conventional powertrains, but also of FCEVs.



Figure I.13.4 Comparison of ParaChoice HD Fleet fraction projections in a) isolation and b) coupled with LD through infrastructure models.

Figure I.13.5 shows the effects of accounting for technology spillover from the LD segment on HD stock fraction, with a two-year delay for HD and a four-year delay for LD. The result is an overall increase in the adoption of all AFV powertrains at the expense of conventional, HE and ISG adoption. A key result

throughout all these cases is that the competition between AFVs is more sensitive than AFVs to conventional vehicles.







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. In FY20 a series of simulations to provide an initial estimate of the impact of LD-HD interaction on AFV adoption in both segments was performed. Initial findings include:

- 1. Accounting for shared infrastructure (i.e., infrastructure model integration) can have a significant effect on AFV adoption in the HD segment. This effect is attributed to the high infrastructure build-out cost in the HD segment.
- 2. Accounting for shared infrastructure has a negligible effect on AFV adoption in the LD segment. Infrastructure build-out costs are a much smaller portion of total cost for LD, so the shared infrastructure effect is small.
- 3. The effect of shared infrastructure and technology spillover results in increased AFV adoption in both segments. As designed, the effect of learning is applied to the technologies of interest as a cost reduction, directly decreasing the purchase costs of the vehicle.
- 4. FCEVs become more competitive after applying learning models due to the purchase cost comprising the majority of the total costs accounted for in this study.

Finally, this work is viewed as a first step into better accounting for the inherently correlated nature of the various on road vehicle segments. As more information about infrastructure build-out costs, technology maturation, and fuel pathways becomes available these projections can be refined.

References

- 1. R. Levinson, D. Manley and T. West, "History vs. Simulation: An Analysis of the Drivers of Alternative Energy Vehicle Sales," SAE Int. J. Alt. Power, vol. 5, no. 2, pp. 357–373, 2016.
- 2. G. E. Barter, "Parametric analysis of technology and policy tradeoffs for conventional and electric light-duty vehicles," Energy Policy, vol. 46, no. 15, 2012.

- 3. Argonne National Laboratory, "GREET Model Greenhouse gases, Regulated Emissions, and Energy use in transportation model," 2016. [Online]. Available: <u>https://greet.es.anl.gov</u>.
- NHTSA National Center for Statistics and Analysis (2006), "Vehicle Survivability and Travel Milage Schedules," 2006. [Online]. Available: <u>https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809952</u>.
- 5. IHS Markit (Formerly Polk Automotive), [Online]. Available: <u>https://ihsmarkit.com/btp/polk.html</u>.
- 6. Argonne National Laboratory, "Autonomie Vehicle Systems Simulation Tool," 2019. [Online]. Available: <u>https://www.anl.gov/es/autonomie-vehicle-system-simulation-tool</u>.
- 7. U.S. Department of Energy, "Alternative Fuel Data Center," 2010–2017. [Online]. Available: https://afdc.energy.gov/data/.
- 8. US Census Bureau, "Vehicle Inventory and Use Survey," 2002.
- 9. American Public Transportation Association, "Public Transportation Fact Book," 2019.
- 10. Oak Ridge National Laboratory, "Freight Analysis Framework V4," 2019. [Online]. Available: <u>https://faf.ornl.gov/fafweb/</u>.
- 11. National Petroleum Council, "Advancing Technology For America's Transportation Future," 2012.
- U.S. Evironmental Protection Agency, "Final Rule for Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles - Phase 2," 2016. [Online]. Available: <u>https://www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-greenhouse-gasemissions-and-fuel-efficiency</u>.
- 13. U.S. Energy Information Administration, "Annual Energy Outlook," 2018.
- 14. Argonne National Laboratory, "Hydrogen Delivery Scenario Analysis Model," 2015. [Online]. Available: <u>https://hdsam.es.anl.gov/index.php?content=hdsam</u>.
- 15. National Renewable Energy Laboratory, "H2A: Hydrogen Analysis Production Models.," 2015. [Online]. Available: <u>https://www.nrel.gov/hydrogen/h2a-production-models.html</u>.
- 16. L. J. Eudy and M. Jeffers, "Battery Electric Bus Progress," Foothills Transit Agency, 2019.
- 17. International Council on Clean Transportation, "Annual Report," 2017.
- S. O'Kane, "The Verge," 13 July 2020. [Online]. Available: <u>https://www.theverge.com/2020/7/13/21322573/fisker-vw-meb-modular-platform-architecture-ocean-suv-apollo</u>. [Accessed 13 July 2020].
- CORDIS EU Research Results, "Automotive Fuel Cell Stack Cluster Initiative for Europe II," CORDIS EU Research Results, 26 November 2018. [Online]. Available: <u>https://cordis.europa.eu/project/id/325335/reporting</u>. [Accessed 1 July 2020].
- 20. S. Yeh and E. S. Rubin, "A centurial history of technological change and learning curves for pulverized coal-fired utility boilers," Energy, vol. 32, pp. 1996–2005, 2007.
- 21. S. Yeh and E. S. Rubin, "A review of uncertainties in technology experience curves," Energy Economics, vol. 34, pp. 762–771, 2012.

- W. J. Abernathy and K. Wayne, "Limits of the Learning Curve," Harvard Business review, September 1974. [Online]. Available: <u>https://hbr.org/1974/09/limits-of-the-learning-curve</u>. [Accessed 19 April 2020].
- A. M. Elshurafa, S. R. Albardi, S. Bigerna and C. A. Bollino, "Estimating the learning curve of solar PV balance-of-system for over 20 countries: Implications and policy recommendations," Journal of Cleaner Production, vol. 196, pp. 122–134, 2018.
- 24. R. Vijayogopal, D. Nieto Prada and A. Rousseau, "Fuel Economy and Cost Estimates for Mediumand Heavy-Duty Trucks," Report to the US Department of Energy, Contract ANL/ESD-19/8, 2019.
- E. Islam, N. Kim, A. Moawad and A. Rousseau, "An Extensive Study on Sizing, Energy Consumption, and Cost of Advanced Vehicle Technologies," Report to the US Department of Energy, Contract ANL/ESD-17/17, 2018.
- 26. Z. Griliches, "The search for R&D spillovers," National Bureau of Economic Research, Cambridge, Massachusetts, 1991.
- 27. M. I. Nadiri, "Innovations and Technological Spillovers," National Bureau of Economic Research, Cambridge, Massachusetts, 1993.
- M. Torero, "ANALYZING THE SPILLOVER MECHANISM ON THE SEMICONDUCTOR INDUSTRY IN THE SILICON VALLEY AND ROUTE 128," in Econometric Society World Congress 2000 Contributed Papers, 2000.
- 29. W. Pan, D. Yang and M. Lin, "Inter-industry Technology Spillover Effects in China: Evidence from 35 Industrial Sectors," China & World Economy, vol. 20, no. 2, pp. 23–40, 2012.
- 30. Solar Energy Industries Association, "Solar Industry Research Data," 2020. [Online]. Available: <u>https://www.seia.org/solar-industry-research-data</u>. [Accessed 29 June 2020].

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I.14 Charging Behaviors and Grid Impacts of Short-Haul Electric Class 8 Semi Trucks (National Renewable Energy Laboratory)

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Non-DOE share: \$0

Project Introduction

Traditionally, plug-in electric vehicles (EVs) have not been considered viable alternatives to diesel trucks for commercial medium- and heavy-duty operations. High range requirements, in particular, are often cited as a major barrier to Class 8 truck electrification, despite surveys suggesting that only around 10% of these trucks have an operating range of 500 miles or more [1]. Consistent technology improvements combined with increased policy support have made the prospect of electrification more attractive to fleet operators, who could benefit from the lower operating costs (i.e., fuel and maintenance) of EVs.

The short-haul trucking segment, where vehicles typically operate within 200 miles of a central depot location, is particularly well-suited for near-term electrification because most charging is expected to occur at the depot, rather than relying on a network of high-power charging stations that add complexity. Recent trends have shown a considerable shift away from long-distance inter-regional (or national) hauls in favor of shorter hauls. These trends have resulted in an increase in the share of short-haul operations and a 37% decrease in the average length-of-haul from 2000–2018 [2], highlighting a growing opportunity for short-haul truck electrification. However, charging remains one of the largest unknowns and sources of anxiety for commercial fleets considering adopting electric vehicles in the near-term. Although significant research has been done on the impacts of added electrical loads on distribution systems, including the impacts of light-duty passenger EV charging, the implications of heavy-duty electric truck charging remains relatively unexplored.

Objectives

The objective of this project is to determine the charging requirements for short-haul electric Class 8 semitrucks charged at depots and to estimate the impacts of various charging strategies on electricity distribution systems. Included in this objective is a clearer understanding of the distribution system upgrades that may be necessary to support truck charging at depots. The project analysis serves to facilitate a dialogue between utilities, manufacturers, fleet operators, and other stakeholders.

Approach

To model realistic duty cycles for short-haul trucking operations, drive cycle (i.e., 1-Hz speed signal) data from three real-world Class 7–8 delivery fleets in the National Renewable Energy Laboratory's (NREL's) Fleet DNA database is leveraged in this study [3]. Daily operating schedules are derived from drive cycle data, disaggregating vehicle days into on-shift and off-shift time periods, where each shift has an associated VMT and vehicles are only available for depot charging when off-shift. With a key initial finding that charging requirements for heavy-duty trucks in short-haul operations can be met at existing commercially available light-duty EV charging power levels, operating schedules are used to develop synthetic electricity demand profiles under three distinct charging strategies:

- **100 kW immediate**: Uncoordinated charging at 100 kW during off-shift periods, starting as soon as possible.
- **100 kW delayed**: Charging at 100 kW as late as possible to fully replenish the battery prior to the subsequent shift, demonstrating the extent to which charging demand can be shifted temporally.
- **Constant minimum power**: Leverages the entire off-shift period to charge at the minimum power necessary to fully replenish the vehicle's battery prior to the subsequent shift, demonstrating the potential to flatten demand by charging at low power levels.

Daily individual EV charging profiles are selected and aggregated into fleet charging demand profiles through simple random sampling with replacement. The average fleet demand profile represents the expected time-resolved electricity demand required for a specific fleet, fleet size (number of EVs), and charging strategy. In addition, the sample fleet profile with the maximum peak power demand is identified and selected for comparison.

To assess the impacts of added depot charging loads, recent public cost data and industry knowledge (from collaborating utilities) are leveraged to develop a taxonomy of electricity distribution system upgrades that may be required to accommodate heavy-duty electric truck charging at depots, including what typically initiates each upgrade, and the costs and lead times associated.

Results

Average fleet demand profiles are produced for combinations of fleet operations (Fleet 1 – beverage delivery, Fleet 2 – warehouse delivery, and Fleet 3 – food delivery), fleet size (10, 50, and 100 EVs), and charging strategy (100 kW Immediate, 100 kW Delayed, and Constant Minimum Power), shown in Figure I.14.1.



Figure I.14.1 Average synthetic depot electricity demand profiles for three heavy-duty electric fleet operations: Fleet 1 – beverage delivery (red), Fleet 2 – warehouse delivery (green), and Fleet 3 – food delivery (blue), including different fleet sizes and charging strategies.

If charging is not managed (i.e., "100 kW immediate" strategy), peak fleet demand coincides with the typical system-level summer peak period. Delaying charging to the latest possible time period shifts peak demand into the early morning, overlapping with the typical winter peak period on the electrical grid. This strategy, however, demonstrates the extent to which 100-kW charging loads can be shifted through managed charging, and the duration of the fleet's peak demand period could be moved to any period within the bounds of the immediate and delayed profiles. The "constant minimum power" charging strategy effectively flattens the fleets' demand, leading to \sim 40–80% reduction in peak power demand. This is accomplished by charging at significantly lower power levels—4.5–15.3 kW/vehicle for Fleet 1, 2.7–22.8 kW/vehicle for Fleet 2, and 1.7–

85.5 kW/vehicle for Fleet 3. These power levels are much lower than what is generally assumed, and the electric vehicle supply equipment (EVSE) capable of supplying such power is commercially available and relatively affordable today.

The taxonomy presented in Table I.14.1 includes the added load (or event) likely to initiate certain upgrades, in addition to the range of expected costs and timelines associated with each upgrade.

Table I.14.1 Taxonomy table of electricity distribution system upgrades for heavy-duty electric truck charging at depots.

Component Category	Upgrade	What Initiates Upgrade	Typical Cost	Typical Timeline	
Customer On-Site	50-kW DCFC EVSE		Procure: \$20,000-36,000/plug Install: \$10,000-46,000/plug		
	150-kW DCFC EVSE	New charger	Procure: \$75,000-100,000/plug Install: \$19,000-48,000/plug	1-3 months	
	350-kW DCFC EVSE		Procure: \$128,000-150,000/plug Install: \$26,000-66,000/plug		
	Install separate meter	Desire to separately meter	\$1,200-5,000		
Utility On- Site	Install distribution transformer	>200 kW added	Procure: \$12,000-175,000	3-8 months	
Distribution Feeders	Extend or upgrade feeders	>5 MW added	\$2-12 million	3-12 months	
Distribution Substation	Add feeder breaker	>5 MW added	~\$400,000	6-12 months	
	Upgrade existing substation	>3-10 MW added	\$3-5 million	12-18 months	
	Build new substation	>3-10 MW added	\$4-35 million	24-48 months	

Conclusions

For the three fleets analyzed in this study, there is ample opportunity for depot charging, with an average of 14 hours per day. By prescribing each vehicle to charge at the lowest power level to fully replenish its battery prior to future shifts (i.e., "constant minimum power" strategy), the fleet's peak demand is significantly reduced (~40%–80% less than for 100-kW charging). Low-power charging is financially beneficial for fleet operators and utilities alike. For utilities, it leads to lower peak demand and a flat, smooth, and predictable demand curve that is less likely to require costly and time-consuming upgrades. Fleet operators also save on the high capital costs of EVSE procurement and installation when they elect for lower-power charging and reduce demand charges. For the three fleets analyzed in this study, 16-, 23-, and 86-kW charging power levels are sufficient, all much lower than is generally assumed. The synthetic fleet depot charging profiles developed in this study will be made publicly available in the near future.

Additional demand from heavy-duty electric truck charging will be met by electricity distribution systems with varying capacity by location and time of day at multiple levels of the system. In some cases, the added demand could exceed the available capacity of a particular component, initiating upgrades. A case study load analysis for select substations in Oncor service territory (Texas) reveals, however, that the majority (78%–86%) of substations considered are capable of supplying 100 battery electric trucks with 100-kW charging each without the need for additional upgrades, and nearly all (89–92%) can handle 100 trucks if charged at their lowest possible power levels (i.e., the "constant minimum power" charging strategy defined in this study). The

taxonomy of upgrades provided in Table I.14.1 is useful for anticipating the potential upstream effects of electrification and providing order-of-magnitude cost and timeline estimates.

Key Publications

1. Borlaug et al. "Heavy-Duty Trucks: Opportunities for Electrification and the Electricity Distribution System Requirements for Depot Charging" completed and will be submitted for journal publication in Q1 FY21.

References

- 1. U.S. Census Bureau, "Vehicle Inventory and Use Survey," U.S. Department of Commerce, 2002.
- 2. Hooper, A. and D. Murray, "E-Commerce Impacts on the Trucking Industry," American Transportation Research Institute, 2019.
- 3. Walkowicz, K., K. Kelly and A. Duran, "Fleet DNA," National Renewable Energy Laboratory, 2016. Accessed February 2020. <u>https://www.nrel.gov/transportation/fleettest-fleet-dna</u>.

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I.15 Minimum Viable Model

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Project Introduction

The purpose of the minimum viable model (MVM) project is to answer transportation questions in the most effective manner. The "minimum viable" model is intended to be a method that can produce results and answer a given question that is sufficient for the needs of the problem, but without additional overhead in complexity, time, or effort that may prevent a model from being effectively used.

The intent of the project is not to provide a single solution for all problems, but rather to look at potential methods to improve modeling for types of transportation questions and improve approaches wherever they are appropriate. In practice, this will look like a toolbox of solutions. Based on the questions and scope that the modelers are seeking to answer, the user would apply specific types of approaches and data sources that would be used to create the minimum viable model to accomplish their task.

Objectives

The project evaluated the effectiveness of new approaches to transportation modelling that answer specific questions. The objective was to find models that optimize for the following attributes:

- 1. Speed: Solutions that can resolve quickly and can look at many scenarios at a much faster rate.
- 2. Appropriate accuracy: Solutions that can provide a level of accuracy and confidence that is appropriate to the questions, scale, and timeline of the questions.
- 3. Ease of implementation: Solutions that can be developed and deployed with limited resources.
- 4. Appropriate scale: Solutions that answer questions at the appropriate scale for the question and solution needs, whether at a community level, urban level, national level, or specialized extent.

The goal of the project was to build a framework and approach rather than to build a specific solution. Future projects would use this framework to construct specific approaches identified in the project.

Approach

This project completed a literature review and analysis of modelling approaches found throughout the transportation community. It examined the types of questions that are often considered for transportation modelling and some of the current modelling approaches to answer these questions. It also looked at some data sources that are currently used in traditional modelling, and it documented limitations of the existing methods.

The project then looked at ways to shift and change the modelling process to help provide a minimum viable solution to any modelling question. It developed a framework for selecting a model approach, examined new methods for modelling—with a particular focus on artificial intelligence (AI) approaches such as machine learning (ML), and looked at new data sources that could be utilized to improve modeling.

Results

The MVM approach is a process for looking at key questions that transportation communities would want to answer, and then using those questions and available resources to create an appropriate model. The recommended method that the team generated would provide a toolbox of solutions that would examine the type of modelling needed and the available data sources. This process would consider the appropriate scope in time and location, the impact of key assumptions, and how to use tools such as AI and high-performance computing.

Model types considered include geospatial analysis, behavioral models (such as activity-based models and agent-based models (ABM)), traffic models (such as mesoscopic and microscopic traffic models), and energy models. Current data sources included geospatial data (such as infrastructure, road grade, and charging infrastructure), travel activity data, traffic operations data, and vehicle operations data.

Figure I.15.1 below presents a schematic of how a user may look at options for developing a model and applying it in different ways.



Figure I.15.1 Schematic steps for choosing a modelling approach

The project's investigation into current and emerging approaches in areas of geospatial, behavior, traffic, and energy modelling identified some new approaches that can significantly aid the current modelling practice. In particular, for each of the domains, application of AI methods offers great promise to reduce the effort needed to train and use a model, as well as increase its accuracy. This project identified ways to apply AI methods to geographic information systems (GIS), mode choice, departure time, destination choice, activity scheduling, traffic assignment, and model simplification.

In addition, new data sources such as open-source infrastructure maps, GPS readers, Google location data, mobile phones, and connected vehicles are providing many new opportunities to utilize more effective data for training AI systems.

Computational advancements such as high-performance computing (HPC) and cloud computing provide the hardware environments in which new, massive data sets can be stored and machine learning models can be trained. In addition, there are options to leverage the cloud as an infrastructure foundation with specific components that run on via HPC, making it feasible to develop a more scalable modelling platform.

The different components of the framework can be applied to transportation-specific problems and questions at different scales. Table I.15.1 shows some possible ways to apply the toolbox to questions regarding automated, connected, electric, or shared vehicles (ACES).

Scope	Automated	Connected	Electrified	Shared	Combination
Large urban areas	ABMs augmented with ML models	Origin- Destination (OD) Trip Tables augmented with sophisticated Dynamic Traffic Assignment (DTA) models	ABMs or Traditional 4-step models coupled with Static assignment	ABMs augmented with ML models and new data sources	ABM + DTA coupled with new data sources and ML models
Small (district sized) communities	OD Trip Tables input to a microsimulation model (+ a few other behavioral modeling components)	Optimization algorithms	OD Trip Tables input to a microsimulation model (+ a few other behavioral modeling components)	OD Trip Tables input to a microsimulation model (+ a few other behavioral modeling components)	OD Trip Tables input to a microsimulation model (+ a few other behavioral modeling components)
Rural and inter-city	Individual trips estimated with new data sources, coupled with reasonable assumptions on aggregate travel behavior (no assignment; only estimation of flows)	OD trip tables estimated with new data sources, coupled with reasonable assumption on aggregate travel behavior (assignment required)	Individual trips estimated with new data sources, coupled with reasonable assumptions on aggregate travel behavior (no assignment; only estimation of flows)	NA	OD trip tables estimated with new data sources, coupled with reasonable assumption on aggregate travel behavior (assignment required)

Table I.15.1 Possible ways to apply MVM to ACES vehicles

Conclusions

Based on a thorough review of literature and data sources, existing as well as emerging, the project team proposed ways to build an MVM framework. The MVM for each technology and spatial context would be selected with an aim to provide a solution that is "good enough" while requiring a reasonable amount of time and effort to develop. This project recommended continued work that would leverage this effort and build a specific MVM tool that would be more accessible to researchers.

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