U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Analysis Program

2021 Annual Progress Report

Vehicle Technologies Office

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Disclaimer

Acknowledgements

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

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

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Acronyms and Abbreviations

21CTP	21st Century Truck Partnership
ACS	American Community Survey
ADOPT	Automotive Deployment Options Projection Tool
AEO	Annual Energy Outlook
AHS	American Housing Survey
ANL or Argonne	Argonne National Laboratory
APR	Annual Progress Report
BA	Balancing Authority
BETO	Bioenergy Technologies Office
BEV	battery electric vehicle
BTU	British thermal unit
C2G	cradle-to-grave
CA	community area
CAV	connected and automated vehicle
CH_4	methane
CI	compression ignition
CNG	compressed natural gas
CO_2	carbon dioxide
COVID	COronaVIrus Disease
CT	current term
DCFC	direct current fast charger
DOE	U.S. Department of Energy
E-drive	electric drive
EEMS	Energy Efficient Mobility Systems (Program)
EERE	Energy Efficiency and Renewable Energy
EIA	U.S. Energy Information Administration
EPA	U.S. Environmental Protection Agency
EPRI	Electric Power Research Institute
EV	electric vehicle
EVI-Pro	Electric Vehicle Infrastructure Projection tool
EVSE	electric vehicle supply equipment
eVTOL	electric vertical takeoff and landing
FAF	Freight Analysis Framework
FASTsim	Future Automotive Systems Technology Simulator
FCEV	fuel cell electric vehicle
Fleet DNA	a clearinghouse of commercial vehicle operations data
FOTW	fact of the week
FY	fiscal year
GBP	Gaussian belief propagation
GCD	great circle distances
GEM	Grid-Integrated Electric Mobility Model
GHG	greenhouse gases
GLH	Google location history

GPS	Global Positioning System
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Transportation model
GridLAB-D	a power distribution system simulation and analysis tool
GWh	gigawatt hour
H2@Scale	DOE initiative to advance affordable hydrogen production, transport, storage, and utilization
H3	a geospatial analysis tool that provides a hexagonal, hierarchical spatial index to gain insights from large geospatial datasets developed by Uber
HD	heavy duty
HDstock	heavy-duty stock (model)
HDV	heavy-duty vehicle
HEV	hybrid electric vehicle
HEVII	Heavy-Duty Electric Vehicle Integration and Implementation
HFTO	Hydrogen and Fuel Cell Technologies Office
Hz	hertz
ICE/ICEV	internal combustion engine/vehicle
ISATT	Integrated Systems Analysis Technical Team
ISG	integrated starter generator
kg	kilogram
kWh	kilowatt hour
LCA	life cycle analysis
LCOD	levelized cost of driving
LDV	light-duty vehicle
LH	location history
LODES	Longitudinal Origin-Destination Employment Statistics
LPG	liquified petroleum gas (or propane)
LT	long term
MA3T	Market Acceptance of Advanced Automotive Technologies model
MDHD/MDHDV	Medium- and Heavy-Duty Vehicle
MD	medium-duty
ML	machine learning
MNL	multinomial logit (model)
mpg or MPG	miles per gallon
mph	miles per hour
MS	Microsoft
MSA	metropolitan statistical areas
MSRP	manufacturer’s suggested retail price
Mt	metric tons
MT	mid-term
MTOW	maximum takeoff weight
MUD	multi-unit dwelling
MWh	megawatt hour(s)
MY	model year
NEAT	Non-Light Duty Energy and GHG Emissions Accounting Tool
NHTS	National Household Travel Survey

NO_x	oxides of nitrogen
NREL	National Renewable Energy Laboratory
OEM	original equipment manufacturer
OpenPATH	Open Platform for Agile Trip Heuristics
OpenVSP	Open Vehicle Sketch Pad
ORNL	Oak Ridge National Laboratory
pax	passenger
PDF	portable document format
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
$PM_{2.5}$	particulate matter with diameters equal to or less than 2.5 micrometers
PM_{10}	particulate matter with diameters equal to or less than 10 micrometers
PNNL	Pacific Northwest National Laboratory
POLARIS	a high-performance, open-source agent-based modeling framework designed for simulating large-scale transportation systems
PopulationSim	population synthesizer
PTW	pump-to-wheel
PUMS	Public Use Microdata Samples
R&D	research and development
REVISE	Regional Electric Vehicle Infrastructure Strategic Evolution
RF	Random Forest (model)
S	Shares (in fractions or percentages)
SAEV	shared, automated electric vehicles
SCE	Southern California Edison
SCM	Smart Charging Management
SCOOT	Screening for City Opportunities Online Tool
SHAEV	shared heavy-duty autonomous and electric vehicles
SMART	Systems and Modeling for Accelerated Research in Transportation
SOC	state of charge
ST	short term
SUV	sport utility vehicle
SVTRIP	Stochastic Vehicle TRIp Prediction
TCO	total cost of ownership
TDP	Transportation Data Program
TEDB	Transportation Energy Data Book
TEEM	Transportation Energy Evolution Modeling
TNC	transportation network companies
UAM	urban air mobility
U.S. DRIVE	Driving Research and Innovation for Vehicle efficiency and Energy sustainability
VC	vehicle cycle
VISION	Verifiable Fuel Cycle Simulation
VMT	vehicle miles traveled
VOC	volatile organic compound
vs.	versus

W	watt
Wh/kg	watt hours per kilogram
VTO	Vehicle Technologies Office
WTP	well-to-pump
WTW	wheel-to-wheel

Executive Summary

During fiscal year 2021 (FY 2021), 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 2021. Each of the progress reports includes project objectives, approach, and highlights of the technical results that were accomplished during the fiscal year (FY).

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Vehicle Technologies Office Overview

Vehicles move our national economy. Annually, vehicles transport 12 billion tons of freight—more than $38 billion worth of goods each day[1]—and move people more than 3 trillion vehicle-miles.[2] Growing our economy requires transportation, and transportation requires energy. The transportation sector accounts for approximately 27% of total U.S. energy needs,[3] and the average U.S. household spends over 17% of its total family expenditures on transportation,[4] making it, as a percentage of spending, the most costly personal expenditure after housing. Transportation is critical to the overall economy, from the movement of goods to providing access to jobs, education, and healthcare.

The Vehicle Technologies Office (VTO) funds research, development, demonstration, and deployment (RDD&D) of new, efficient, and clean mobility options that are affordable for all Americans. VTO leverages the unique capabilities and world-class expertise of the National Laboratory system to develop new innovations in vehicle technologies, including advanced battery technologies (including automated and connected vehicles as well as innovations in efficiency-enhancing connected infrastructure); innovative powertrains to reduce greenhouse gas and criteria emissions from hard-to-decarbonize off-road, maritime, rail, and aviation sectors; and technology integration that helps demonstrate and deploy new technology at the community level. Across these technology areas and in partnership with industry, VTO has established aggressive technology targets to focus RDD&D efforts and ensure there are pathways for technology transfer of federally supported innovations into commercial applications.

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 advances technologies that assure affordable, reliable mobility solutions for people and goods across all economic and social groups; enable and support competitiveness for industry and the economy/workforce; and address local air quality and use of water, land, and domestic resources.

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 Technologies 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) 2021. The APR presents descriptions of each active project in FY 2021, including funding, objectives, approach, results, and conclusions.

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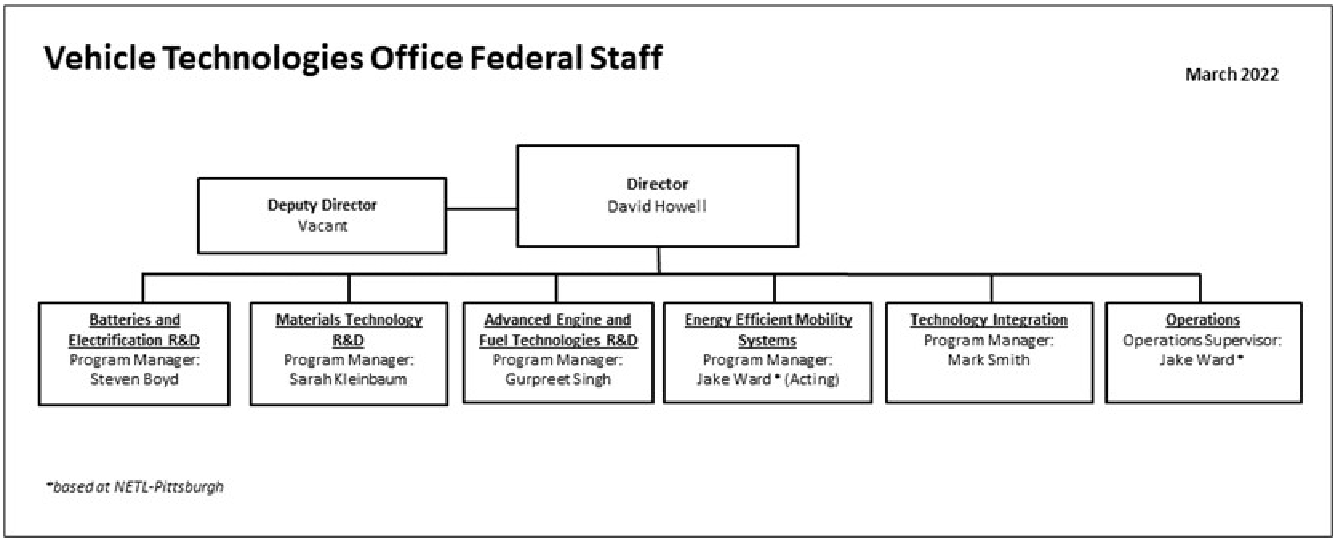
[1] U.S. Department of Transportation, Freight Analysis Framework Version 5.0 Data Tabulation Tool.
[2] U.S. Department of Transportation, March 2022 Traffic Volume Trends, Figure 1.
[3] U.S. Energy Information Administration. Monthly Energy Review, 2022, https://www.eia.gov/totalenergy/data/monthly/index.php.
[4] Davis, Stacy C., and Robert G. Boundy. Transportation Energy Data Book: Edition 39. Oak Ridge National Laboratory, 2020, https://doi.org/10.2172/1767864.

Organization Chart



Analysis Program Overview

Introduction

Achieving deep decarbonization in transportation will require vehicle efficiency improvements, low lifecycle carbon-intensity fuels and related infrastructure, and overall system-wide improvements in the transportation system, particularly those that have the potential to reduce total annual vehicle miles traveled (VMT). VTO funds research, development, demonstration, and deployment 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 technological, 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 DOE's 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 system connectivity, greater penetration of shared vehicles and micromobility, 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 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, how will charging infrastructure needs evolve? How will use of these vehicles impact the electricity grid, and vice versa? How can this infrastructure be made available to consumers across the socioeconomic 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—and modes 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?

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 insights into transportation and energy use problems for a broad range of internal and external stakeholders.

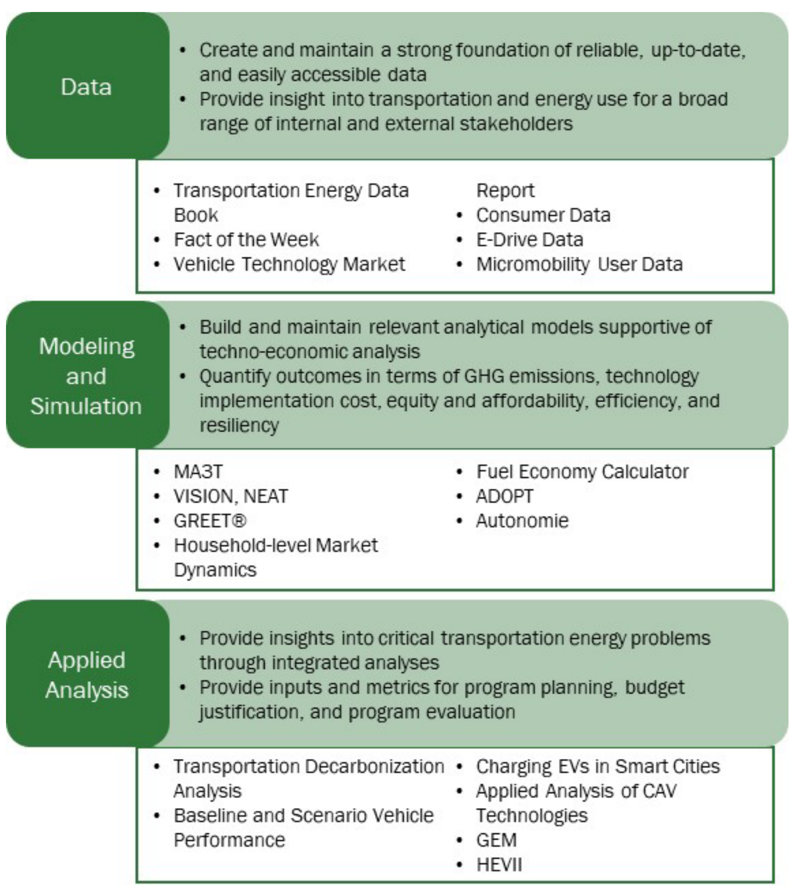
To achieve these goals, the Analysis Program supports activities with the following three broad objectives:

- Create and maintain a strong foundation of data.
- Build, maintain, and exercise relevant analytical models.

Execute insightful integrated analyses that provide greater understanding of critical transportation energy problems.

Program Organization Matrix

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



For FY 2021, several applied analysis activities within VTO's Systems and 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 2021 Annual Progress Report and the EEMS FY 2021 Annual Progress Report.

I Analysis Program Project Portfolio

I.1 Distributions of Real-world Vehicle Travel (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $150,000	DOE share: $150,000	Non-DOE share: $0
Project Funding (FY20-FY21): $300,000	DOE share: $300,000	Non-DOE share: $0
Total Expected Project Funding: $450,000	DOE share: $450,000	Non-DOE share: $0

Project Introduction

A firm understanding of vehicle ownership and operational behavior is necessary to fully assess the economic and environmental impacts of that vehicle. 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 VMT, considering vintage, vehicle characteristics, and demographic characteristics; 2) quantifies 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 to determine typical length of time that different types of vehicles stay on the road. These results will be broadly shared to better inform calculations by DOE and others.

Approach

This paper explores the non-homogeneous driving behavior of passenger vehicles, with the goal of understanding with greater resolution the energy consumption of the light-duty vehicle fleet along with the representative consumer costs. The typical metric used for driving behavior is vehicle miles traveled, or VMT.

Since fuel consumption is largely proportional to mileage, an understanding of VMT is necessary to estimate lifetime energy consumption. In turn, operational costs are largely proportional to fuel consumption, and so estimates of consumer costs are strongly dependent on calculations of VMT.

This project uses light-duty vehicle travel data from the National Household Travel Survey (NHTS) and state odometer reading records to explore the nationwide distribution of VMT [1]. In prior analysis, this distribution has been examined as a function of multiple parameters related to vehicle age, vehicle characteristics, and demographics. The project also considers vehicle survivability, comparing the number of vehicles registered [2] with original vehicle sales [3],[4],[5] to see how many of those vehicles are still operational today. Per-vehicle VMT and scrappage rates have been correlated with other variables in order to determine how VMT and scrappage are linked to demographic characteristics.

In this project, 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 will 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. Using results for light-duty vehicle characteristics from the Energy Information Administration Annual Energy Outlook 2020 [6] in the Verifiable Fuel Cycle Simulation (VISION) model [7], this project quantifies the energy variations that arise from consumers with non-homogeneous driving behavior purchasing vehicles that they expect to minimize their driving costs.

Results

This project is modeling vehicle survivability using a logistic function, popular for population dynamics, following Greene and Chen [8]. For each vehicle make and model, the survivability was modeled using the logistic function: $Survivability = 1 - \left(1 + e^{-\beta\left((x_0 - x) - t_0\right)}\right)^{-1}$, where β represents a rate parameter, t_0 is a variable to represent the median lifetime of a model, x_0 represents the current year, and x represents the model year. The rate parameter shows how sharp the "S"-shape is of the logistic. The logistic function solves for t_0 and β by a least squares fit between the logistic function and the implicit survivability found by dividing that model year's registrations in the current year by its sales in the model year. Figure I.1.1 shows a logistic curve for the implicit survivability of all vehicles for which original sales data was available. The x-axis represents the number of years between the data snapshot (2021) and the calendar year of sales (assumed as the vehicle model year in this study). The y-axis represents the ratio of currently registered vehicles to originally sold vehicles.

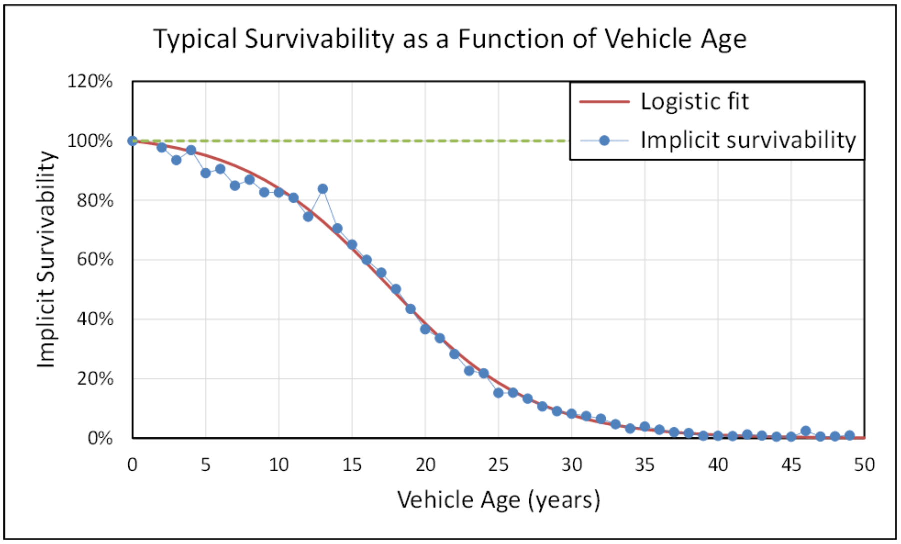

Figure I.1.1 Implicit vehicle survivability as a function of vehicle age. Source: ANL

This project finds that the shape of this logistic curve varies as a function of vehicle size or powertrain. Table I.1.1 shows the median lifetime and rate factor for different size classes (car, pickup, sport utility vehicle, and van), and Table I.1.2 shows the information for different powertrains (conventional internal combustion engine vehicle (ICEV), hybrid electric vehicle (HEV), battery electric vehicle (BEV), and plug-in hybrid electric vehicle (PHEV)). Trucks generally have slower scrappage than cars. Specifically, pickup trucks have the longest life, followed by sport utility vehicles (SUV). Cars and vans both have a modeled median lifetime of 16.2 years. This table also shows that HEV have a modeled vehicle lifetime longer than the average vehicle, while BEV and PHEV each have median lifetimes shorter than conventional vehicles. It is worth noting that most HEV, BEV, and PHEV which have been sold in the United States are cars, which exhibit a shorter lifetime than light trucks. Further, because of the shorter availability of alternative-fuel vehicles, these vehicles have fewer model years for the curve fits, which may skew the numbers toward a lower lifetime.

Table I.1.1 Modeled Vehicle Scrappage Rates Aggregated by Size Class

Vehicle size class	Median Lifetime (years), t_0	Rate Factor, β	Number of vehicles	Model years
All vehicles	17.6	0.199	228 million	1972 – 2019
Car	16.2	0.200	92 million	1972 – 2019
Pickup Truck	22.1	0.166	48 million	1973 – 2019
Sport Utility Vehicle	18.6	0.197	75 million	1976 – 2019
Van	16.2	0.232	13 million	1983 – 2019

Table I.1.2 Modeled Vehicle Scrappage Rates Aggregated by Powertrain

Vehicle powertrain	Median Lifetime (years), t_0	Rate Factor, β	Number of vehicles	Model years
All vehicles	17.6	0.199	228 million	1972 – 2019
HEV	18.3	0.152	4.3 million	2000 – 2019
PHEV	10.7	0.632	0.6 million	2011 – 2020
BEV	13.4	0.183	1.0 million	2011 – 2020

There is a likely interplay between end-of-life vehicle behavior and the total cost of ownership (TCO). A state-by-state analysis was performed to examine spatial variations in vehicle age, where age is a proxy for vehicle scrappage. The full correlation matrix is shown in Figure I.1.2. This analysis found that vehicle age is negatively correlated with median income and fuel economy; newer vehicles have better fuel economy and are more likely to be purchased in higher-income locations. VMT is weakly negatively correlated with fuel price, and reasonably correlated to income. At the end of vehicle life, average vehicle age is correlated to the presence of state inspections for emissions or safety. These stricter state requirements may require vehicles to have repairs that are viewed as not economical, leading people to decide to scrap their vehicle (or sell across state lines).

	Number of vehicles	Average Age	Average MPG	% HEV/PEV	Annual Snowfall (in)	Registration fee (age 12)	Emissions Inspection	Safety Inspection	Fuel Price	Average VMT	Median Income
Number of vehicles	1.00	-0.40	0.42	0.49	-0.32	0.12	0.09	0.07	0.39	-0.18	0.07
Average Age	-0.40	1.00	-0.78	-0.27	-0.06	-0.01	-0.40	-0.48	-0.10	-0.18	-0.48
Average MPG	0.42	-0.78	1.00	0.64	0.01	0.06	0.52	0.36	0.41	0.06	0.55
% HEV/PEV	0.49	-0.27	0.64	1.00	0.02	0.35	0.40	0.03	0.80	-0.06	0.52
Annual Snowfall (in)	-0.32	-0.06	0.01	0.02	1.00	0.21	0.19	0.08	0.09	0.14	0.42
Registration fee (age 12)	0.12	-0.01	0.06	0.35	0.21	1.00	0.06	-0.32	0.39	0.11	0.39
Emissions Inspection	0.09	-0.40	0.52	0.40	0.19	0.06	1.00	0.37	0.31	-0.04	0.43
Safety Inspection	0.07	-0.48	0.36	0.03	0.08	-0.32	0.37	1.00	-0.14	-0.02	0.11
Fuel Price	0.39	-0.10	0.41	0.80	0.09	0.39	0.31	-0.14	1.00	-0.29	0.37
Average VMT	-0.18	-0.18	0.06	-0.06	0.14	0.11	-0.04	-0.02	-0.29	1.00	0.50
Median Income	0.07	-0.48	0.55	0.52	0.42	0.39	0.43	0.11	0.37	0.50	1.00

Figure I.1.2 Correlations of different demographic factors by state with vehicle characteristics, including vehicle age and fuel economy. Source: ANL

Total cost of ownership can be quantified rigorously based on assumptions of driving behavior, as was done in a recent VTO Analysis-funded project [9]. Using the framework that was presented in that work, this project compared LCOD for different vehicles, including hypothetical vehicles modeled to be available in the future and others that are available for purchase today. Figure I.1.3 shows the total cost of ownership for real-world model year 2019 small sport utility vehicles, purchased used after three years (e.g., in late 2021 or 2022), and held for seven years. The vehicles modeled are representative of those that were on the market in 2019. Vehicles driven in the 15th percentile of driving intensity, as determined by an analysis of the NHTS data [1] (approximately 6,000 miles per year) show HEV to be the lowest cost powertrain at 57 cents per mile, followed by conventional ICEV at 61 cents per mile, with the BEV at 75 cents per mile. The BEV is the highest cost option due to the higher purchase value at three years after original purchase as well as the cost to purchase charging equipment for home use. For vehicles driven in the 50th percentile (approximately 14,000 miles per year), HEV remain the lowest cost option at 37 cents per mile, followed by BEV at 40.8 cents per mile and ICEV at 41.5 cents per mile. In this case, the greater driving distance leads to a greater amortization of the initial purchase cost, lowering the per-mile LCOD for each powertrain. Finally, for vehicles driven in the 85th percentile (approximately 25,000 miles per year), BEV are the cheapest option at 28.2 cents per mile, followed closely by HEV at 28.5 cents per mile, with ICEV again presenting the highest cost option, with an LCOD of 33.5 cents per mile.

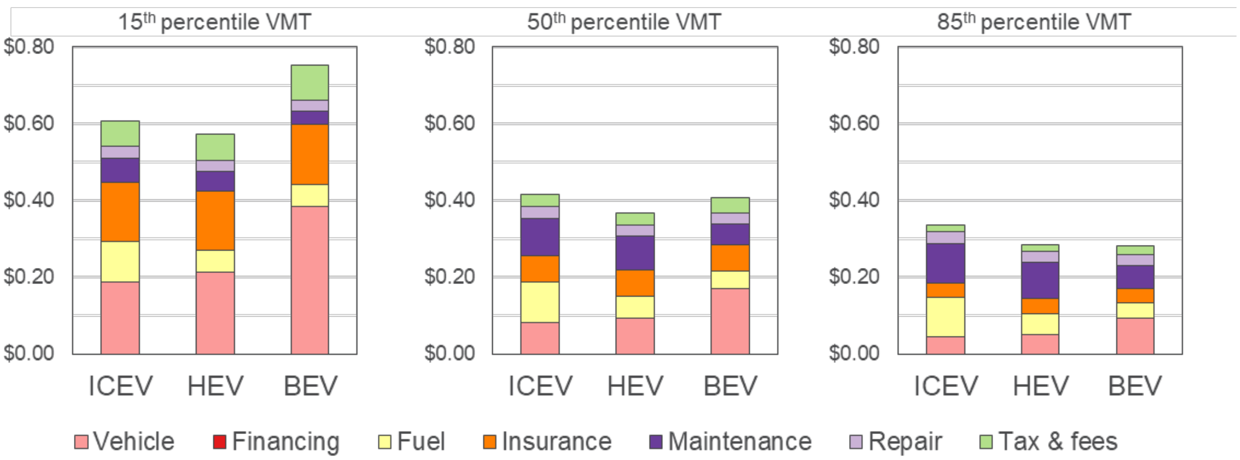

Figure I.1.3 LCOD for three different powertrains for small sport utility vehicles, representative of model year 2019 vehicles purchased at three years old and held for seven years. Source: ANL

As seen in Figure I.1.3, LCOD skews more toward operational costs than vehicle purchase costs when driving distances are farther. It is therefore likely that rational consumers who drive more than average will aim to minimize operational costs and therefore disproportionately use more fuel-efficient vehicles and alternative-fuel vehicles. Figure I.1.4 shows sales shares across the population as a function of VMT percentile for a scenario in which all drivers are equally likely to choose a given vehicle and a second scenario in which the probability of purchasing a specific vehicle is proportional to e^{-kx}, where k is a proportionality constant and x is the total cost of driving per mile. Inputting these scenarios into the VISION model, the baseline scenario yielded a calculated light-duty vehicle (LDV) energy consumption of 9.45 quadrillion British thermal units (BTUs) (quads) through 2050, while the second scenario used 8.95 quads over the same timeframe. In other words, heavier electrification in the most intense segment leads to moderately lower total energy consumption (-5.3%) and this is accompanied by much higher LDV electricity charging (+80%).

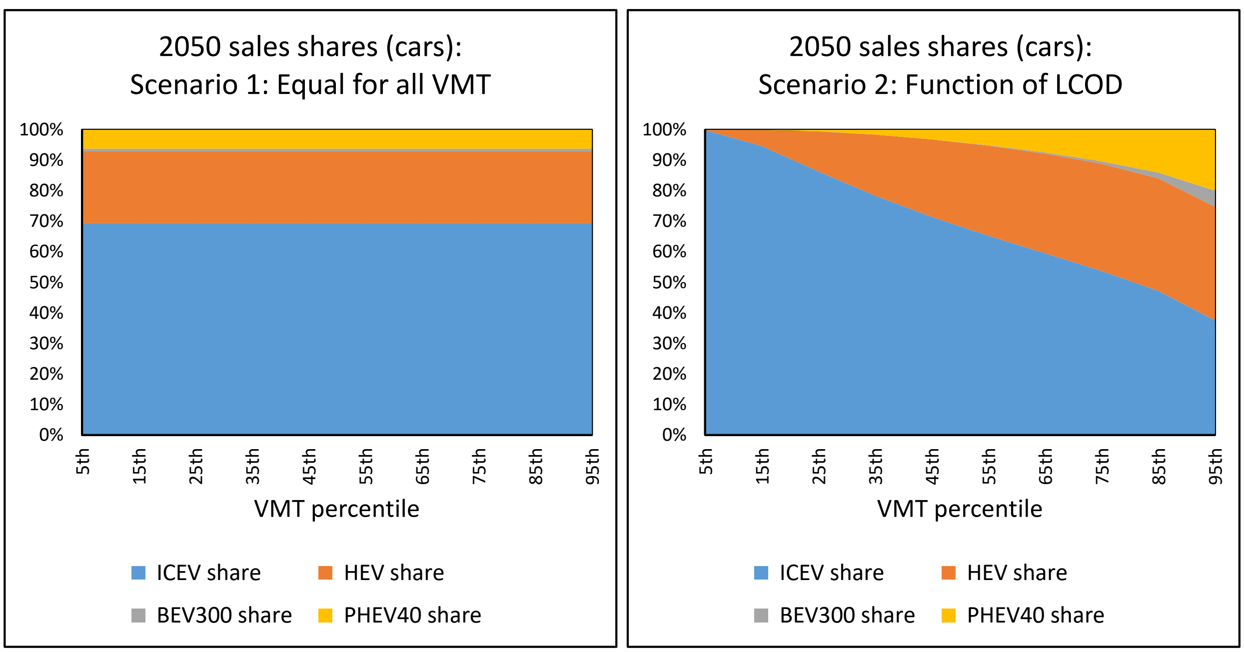

Figure I.1.4 Sales shares for cars in 2050 for two scenarios of consumer vehicle choice. Source: ANL

Conclusions

This project has found broad distributions in vehicle travel, which 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 many vehicles drive significantly more or significantly less than the "average" vehicle, with approximately 13% of all vehicles driving more than twice as much as the median, and 20% of all vehicles driving less than half as much as the median. This project has begun to understand how vehicle energy consumption is related to vehicle survivability as well.

Data from this task has been used to quantify vehicle TCO and energy consumption based on inputs from parallel DOE-sponsored research. As described above, vehicle lifetime and typical annual travel are key assumptions which impact TCO and LCOD calculations. This project uses the VISION model 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.

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Acknowledgements

Data processing and analysis was assisted by Matthews Cribioli, a student researcher from the University of California, Irvine, and by Rebecca Schwartz, a student researcher from Brown University. Joann Zhou of Argonne National Laboratory and Raphael Isaac of Energetics each gave valuable feedback and technical suggestions for this project.

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $100,000	DOE share: $100,000	Non-DOE share: $0
Project Funding (FY20-FY21): $200,000	DOE share: $200,000	Non-DOE share: $0
Total Expected Project Funding: $300,000	DOE share: $300,000	Non-DOE share: $0

Project Introduction

This project uses life cycle analysis (LCA) to estimate the cradle-to-grave (C2G) greenhouse gas (GHG) emissions and costs of LDV and medium- and heavy-duty vehicles (MDHDVs) considering current and future technologies. For this analysis, Argonne configured the Greenhouse gases and Regulated Emissions and Energy use in Technologies (GREET) model to evaluate the lifecycle GHG emissions of current and future technology pathways of petroleum and renewable gasoline for ICEVs and HEVs, conventional and renewable natural gas for CNG ICEVs, diesel for ICEVs, corn and cellulosic ethanol for ICEVs, steam-methane reforming and renewable hydrogen for fuel cell electric vehicles (FCEVs), and current and low carbon electricity for PHEVs and BEVs. Cost data were obtained from the literature and Department of Energy modeling for both current and future vehicle powertrain and fuel conditions.

Objectives

The goal of this research is to identify the C2G GHG emissions and costs associated with current (2020) and future (2030–2035) LDV and MDHDV technologies, considering a variety of different fuel pathways. The completed analysis so far covers LDV technologies. Utilizing gasoline-powered sedans and small SUVs in the United States as the baseline, the analysis evaluated the GHG reduction potential and the cost of such reductions using future cost projections for conventional fuels, biofuels, electricity from different resources, and hydrogen produced in several different ways. Vehicle-fuel combinations could thus be identified that offer significant GHG reductions in the most economically favorable manner.

Approach

To assess lifecycle GHG emissions, this study considers emissions associated with both the fuel cycle and the vehicle cycle. The C2G GHG emissions assessment was carried out by expanding and modifying the GREET model with inputs informed by industry expertise. GREET calculates the energy use and emissions associated with production, transportation, distribution, and use of fuel during vehicle operation as well as those associated with the production of the vehicle and the end of life decommissioning and recycling of vehicle components. The cost analysis considered the cost of producing fuels and of producing and operating the vehicle while accounting for depreciation and the time value of money. Relevant data on energy use, emissions, and cost was obtained from agency projections (such as those by the U.S. Energy Information Administration (EIA)), literature, and modeling for both current and future conditions.

Results

Current and future vehicle powertrain technologies were evaluated for current and future fueling pathways, respectively, to determine their resultant GHG emissions on a life cycle basis and the costs of these vehicle-fuel combinations. Results indicated that future vehicle technology developments alone, will be capable of reducing GHG emissions in a meaningful way, with a 25% reduction from the Current to the Future Gasoline ICEV vehicle. In fact, the Current HEV may perform equally relative to Future ICEV. At the same time, the results demonstrate that achieving deep GHG reduction will need coupled improvements in vehicle technologies along with decarbonized fueling pathways, as seen by the vertical gray arrows in Figure I.2.1. From a cost perspective, the levelized cost of driving (owning and operating cost) over the lifetime of the battery EV is comparable to that of an ICEV, ranging from a 14% cost reduction (200-mile range EV) to a 4% cost increase (400-mile range EV).

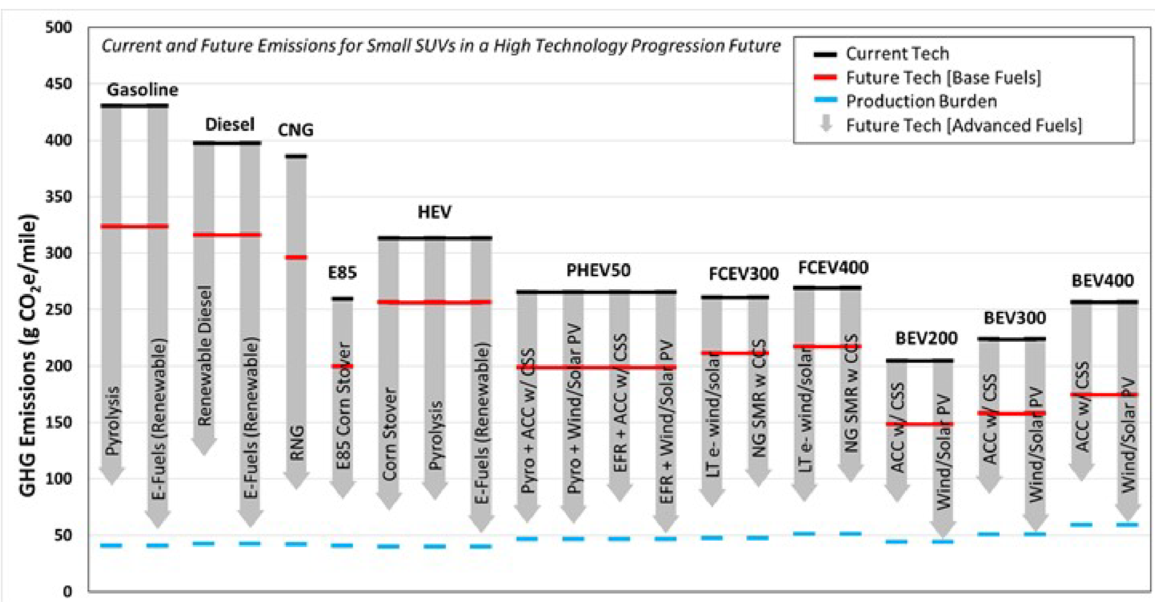

Figure I.2.1 GHG emissions for Current and Future (2030-2035) Small SUVs across multiple fueling pathways. Source: ANL

Conclusions

This study so far has found that technology advancement on the vehicle side will be an important facilitator of GHG reduction for LDVs. Both efficiency improvement and powertrain switching could lead to meaningful GHG reductions for these vehicles . However, to achieve deep decarbonization it will be necessary to advance fueling technologies such that the energy sources, themselves, have much reduced CO_2 contents. Results also suggest that the cost of reduction for battery electric vehicles are likely to make battery EVs competitive with gasoline ICEVs on a levelized cost of driving basis.

Key Publications

Elgowainy A., Kelly, J.C., Wang, M., 2020, “Life Cycle Greenhouse Gas Emissions for Small Sport Utility Vehicles.” (U.S. DOE Record # 21003).

Kelly, J.C., et. al., ”Cradle-to-Grave Lifecycle Analysis of U.S. Light-Duty Vehicle-Fuel Pathways: A Greenhouse Gas Emissions and Economic Assessment of Current (2020) and Future (2030-2035) Technologies.” In Preparation.

Acknowledgements

The team acknowledges support from U.S. DRIVE’s ISATT, including experts from the U.S. Department of Energy, the energy and auto industries, and national laboratory researchers.

I.3 Medium- and Heavy-Duty Vehicle Manufacturing and Life Cycle Analysis (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $175,000	DOE share: $175,000	Non-DOE share: $0
Project Funding (FY20-FY21): $350,000	DOE share: $350,000	Non-DOE share: $0
Total Expected Project Funding: $525,000	DOE share: $525,000	Non-DOE share: $0

Project Introduction

To date, LDVs have been modeled on a C2G basis within Argonne's GREET (Greenhouse gases and Regulated Emissions and Energy use in Technologies) LCA model. Well-to-wheels (WTW) analyses of MDHDVs have also been developed within GREET. However, the vehicle cycle of MDHDVs has not been modeled or evaluated in depth. Yet, an unladen long-haul Class 8 tractor-trailer ICE truck can weigh up to 26,000 pounds, comprised largely of steel, cast iron, aluminum, and various polymers, and may represent a significant energy and emissions burden. But the lifetime VMT of these trucks may mitigate the large initial energy use and emissions burdens on a per-mile basis. Similarly, the large payload these trucks can carry may mitigate the initial energy and emissions burdens on a per-ton-mile basis. On the other hand, electrification of MDHDVs may have very different vehicle-cycle energy and emission implications than conventional ICEVs since vehicle batteries can have a significant energy and emissions burden during production.

Objectives

The goal of this project was to identify the total vehicle material composition of Class 6 pickup and delivery trucks, and Class 8 day-cab and sleeper-cab trucks, inclusive of the tractor and trailer, across ICEV, HEV (for Class 6), and BEV powertrains. Additionally, we sought to understand the replacement timeline for common elements, such as tires, oil, batteries, etc. The primary desired outcome of this effort was the integration of these vehicles within the GREET model, thereby allowing for C2G analyses of MDHDVs.

Approach

Argonne modeled and evaluated vehicle and component weights, and material compositions for MDHDVs. Vehicles' payload and lifetime vehicle miles traveled (VMT) were assessed to amortize material and manufacturing burdens on a per-mile and per-ton-mile basis so that they can be additive to the fuel-cycle WTW energy use and emissions for a full C2G LCA. Component replacement over vehicle lifetime was also assessed and incorporated. Battery chemistry and the full battery systems appropriate for each BEV vehicle class were evaluated and incorporated. The modeling effort used a bottom-up and top-down approach to identify the material composition of all MDHDV components along with their weights. From the bottom-up perspective, weight, and material composition data for MDHDV component systems were compiled and aggregated from information on individual parts and subsystems. Data sources included: (a) Technical literature (journal and conference papers, and technical reports); (b) Company literature from manufacturers and sellers of individual parts, subsystems, and/or component systems used in present-day versions of the selected MDHDVs; (c) the existing GREET model for LDVs. From the top-down perspective, modeling outputs from Islam et al. [1] were used to size the component systems in order to align energy consumption profiles of the same vehicles.

Results

Vehicle cycle material composition inventories were developed for MDHDVs, incorporated into the GREET model, and then evaluated to better understand life cycle impacts. Integration of these vehicle compositions into GREET allows comparison of the vehicle cycle (VC) with the vehicle's WTW—aka "fuel cycle"—components (i.e., well-to-pump (WTP), or fuel/energy production and delivery, and pump-to-wheel (PTW), or operations). Figure I.3.1 shows initial results of this analysis, which assumes that BEVs charge on the average U.S. electrical grid and assumes lifetime vehicle miles traveled of 300k and 1 million for the Class 6 and Class 8 vehicles, respectively. Also note that Class 6 BEVs have one lifetime traction battery, while Class 8 have two.

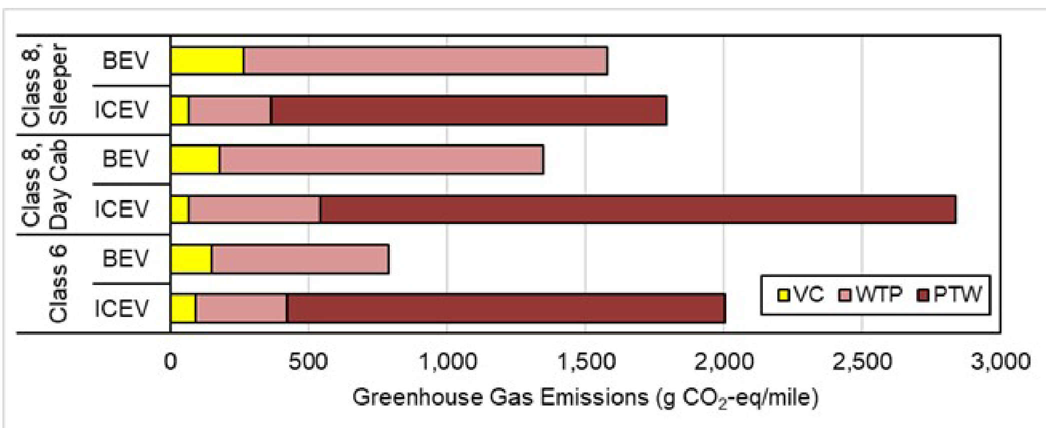

Figure I.3.1 Life cycle GHG emissions for MDHDVs on a per-mile basis. Note that the lifetime miles traveled are 300k for a Class 6 vehicle and 1 million for Class 8 vehicles. Source: ANL

Conclusions

The GREET model was expanded to include an extensive mass and material composition formulation for MDHDVs. This allows for C2G analysis when coupled with the fueling WTW modeling that is already a fundamental component of the GREET model. Initial results indicate that, on a C2G basis, the MDHDV vehicle cycle represents a relatively small portion of the total life cycle GHG emissions for ICEVs (~2%–5%) but a larger portion for BEVs (~13%–19%).

Key Publications

Iyer, R.K., et al., 2021, "Vehicle-Cycle Inventory for Medium- and Heavy-Duty Vehicles." Argonne National Laboratory publication ANL/ESD-21/18.

Iyer, R.K., et al., 2022, "Life-Cycle Analysis of Class 8 Regional and Long-Haul Diesel and Electric Truck Production." Presentation at the Transportation Research Board 101st Annual Meeting, January 9–13, 2022, Washington, D.C.

References

1. Islam, E.S. et al., 2021, "A Detailed Vehicle Modeling and Simulation Study Quantifying Energy Consumption and Cost Reduction of Advanced Vehicle Technologies Through 2050." Argonne National Laboratory (ANL/ESD-21/10).

I.4 Seasonal and Sectoral Variations of Consumption-Based Regional Electricity Characteristics and Regional Well-to-Wheels Analysis of Medium- and Heavy-Duty Vehicle/Fuel Systems (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $125,000	DOE share: $125,000	Non-DOE share: $0
Project Funding (FY20-FY21): $300,000	DOE share: $300,000	Non-DOE share: $0
Total Expected Project Funding: $425,000	DOE share: $425,000	Non-DOE share: $0

Project Introduction

An accurate picture of electricity characteristics, which vary significantly by region, are crucial for the assessment of the environmental impacts of BEVs at the regional level. Due to the fact that there are frequent electricity interchanges among regions in the U.S., regional electricity characteristics as derived from a consumption-based perspective might differ significantly from those characterized solely based on electricity generation. In FY 2020, Argonne developed an integrated modeling system that considers electricity generation, consumption, and imports and exports among 78 balancing authorities (BAs) in the U.S., Canada, and Mexico in order to characterize consumption-based regional electricity characteristics at an annual level. In FY 2021, Argonne expanded the analysis to include the sectoral and the monthly levels, since there are significant variations in electricity use by sector as well as in electricity generation/interchanges by month. Argonne also conducted a preliminary WTW comparison of a diesel ICEV and BEV technologies for medium-duty and heavy-duty (MDHD) trucks at the state level from the consumption-based electricity perspective.

Objectives

The objectives of this project were to (1) develop consumption-based electricity mixes, energy use intensities, and emissions intensities of both greenhouse gases (both GHGs as a whole and also CO_2, methane, and nitrous oxide separately) and air pollutants (NO_x, sulfur dioxide, carbon monoxide, VOC, PM_{10}, $PM_{2.5}$, black carbon, and organic carbon) for regional electricity use in the U.S. by sector and by month, and (2) compare WTW energy use and emissions of diesel ICEV and BEV technologies for MDHDVs at the state level using the developed consumption-based electricity characteristics.

Approach

Argonne processed, compiled, and estimated all relevant data at the monthly level, including electricity generation and fuel consumption by fuel type and by power plant, emissions of GHGs and air pollutants by power plant, electricity interchanges among BAs, and electricity sales by BA and by sector (including residential, commercial, industry, and transportation) in the year 2017. Using Argonne's GREET.Net software, these collected data were incorporated into the network-based modeling system for the entire North American electrical network and consumption-based regional electricity mixes, energy use intensities, and emission intensities of electricity by month and by sector in the U.S. were also derived.

Argonne expanded its recent national WTW analysis of battery MDHDVs [1] to the state level using the consumption-based regional electricity characteristics developed in this project. Six types of MDHDVs were considered, including Class 8 long-haul combination, Class 8 short-haul combination, Class 8 refuse, Class 6, medium heavy-duty vocational, Class 4 light heavy-duty vocational, and Class 2 pickup trucks and vans. Fuel economy values for these MDHDV classes are from Argonne's Autonomie model simulations.

Results

Figure I.4.1 shows monthly GHG emission intensities of electricity by BA in 2017. At the national level, electricity GHG emission intensities are relatively high in summer and winter and low in spring and autumn. Moreover, significant seasonal variations in electricity characteristics are evident at the regional level, from both the consumption-based and generation-based perspectives. An additional key finding from this data is that, as had been hypothesized, consumption-based electricity results differ from generation-based ones for most regions in the U.S., particularly for small BAs, due to frequent interregional electricity interchanges.

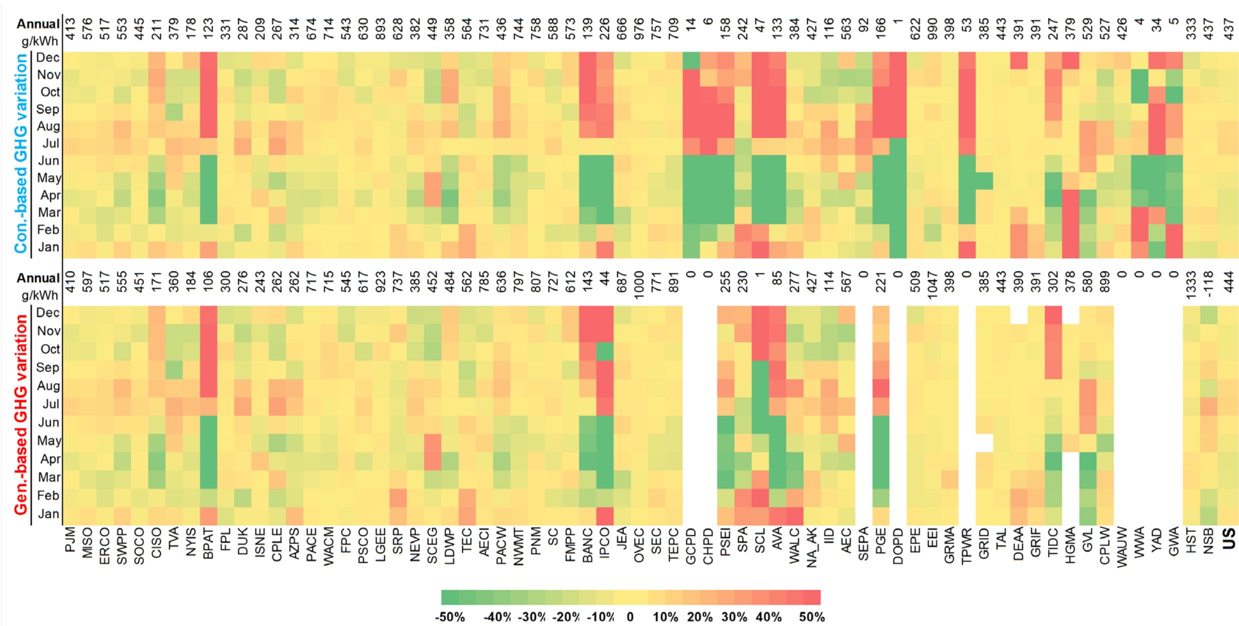

Figure I.4.1 Monthly variations of generation-based (bottom) and consumption-based (top) GHG emission intensities of electricity relative to the annual averages by BA in 2017. Some BAs do not have generation-based results because they solely act as nodes in the grid. (Transmission losses are not taken into account.). Source: ANL

Similar results are also available for electricity mixes, energy use intensities, and emission intensities of individual GHGs and air pollutants for all BAs.

Figure I.4.2 shows sectoral variations in consumption-based GHG emission intensities of electricity by state in 2017. There are moderate differences in consumption-based electricity results among sectors within most states. At the national level, GHG emission intensities of electricity used in the transportation, commercial, and residential sectors were 31%, 3%, and 1% lower than the average of all-sector electricity use, respectively. Electricity consumed in the industry sector was 6% more GHG-intensive than the all-sector average. It is important to note that the electricity used in the transportation sector does not include that used to charge on-road plug-in electric vehicles, but it does include the electricity used to power railroads and railways.

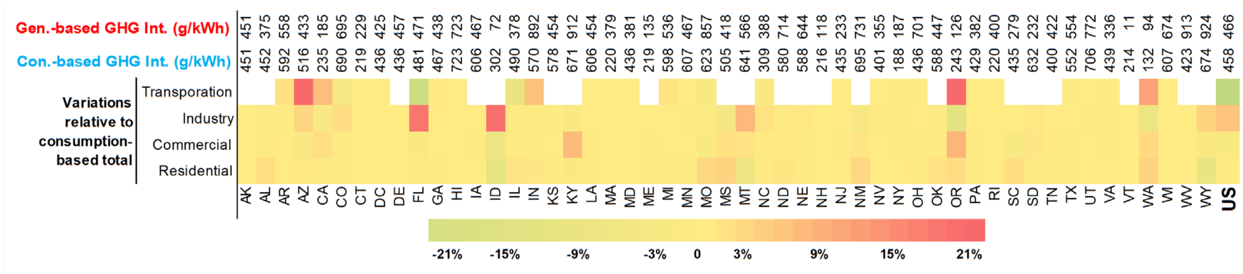

Figure I.4.2 Generation-based (numeric only) and sectoral consumption-based GHG emission intensities of electricity by state in 2017. (Transmission losses are taken into account for both consumption and generation.). Source: ANL

Similar results for electricity mixes, energy use intensities, and emission intensities of specific GHGs and air pollutants are also available.

Figure I.4.3 shows a WTW GHG emissions comparison, by state, between BEVs and diesel ICEVs for Class 8 long-haul and Class 6 MDHD vocational trucks, presumably as deployed in 2017. Consumption-based electricity characteristics are used in the analysis. There are large WTW emissions variations for BEVs at the state level. From a consumption-based electricity perspective, Class 8 long-haul BEVs have higher WTW GHG emissions than their ICEV counterparts in 27 states. Due to higher weighting from the Air Resources Board cycle (i.e., urban cycle), Class 6 MDHD BEVs have less WTW GHG emissions than their ICEV counterparts in all states.

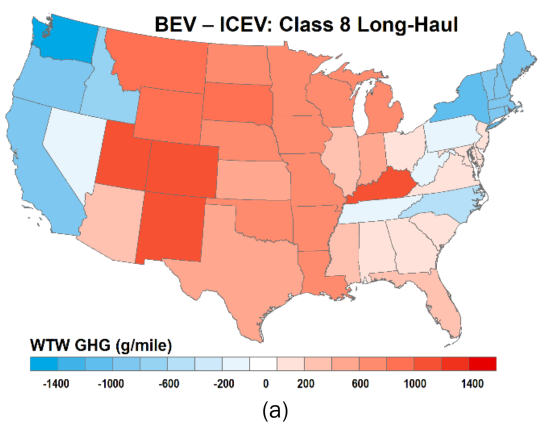

Figure I.4.3 Differences between WTW GHG emissions of BEV and diesel ICEV for (a) Class 8 long-haul and (b) Class 6 MDHD vocational trucks at the state level in 2017. Source: ANL

In nearly all continental U.S. states, Class 8 long-haul and Class 6 MDHD BEVs have less WTW NO_x emissions than their ICEV counterparts. Shifting from ICEV to BEV would increase WTW PM_{10} emissions across all MDHDV types except for in states with a cleaner consumption-based grid (e.g., the northwestern and northeastern states).

Similar results are available for WTW emissions of individual GHGs and air pollutants for all six types of MDHD trucks.

Conclusions

The previously developed consumption-based regional electricity characteristics analysis was expanded to the sectoral and the monthly levels, which improves the representation of regional electricity use in the environmental assessment of BEVs at the regional level. Whether MDHD BEVs have WTW environmental benefits over their ICEV counterparts varies by vehicle type, state, and the pollutants targeted.

Key Publications

Ankathi, S., Lu, Z., Zaimes, G., Hawkins, T., Gan, Y., Wang, M. "Greenhouse gas emissions from the global transportation of crude oil: current status and mitigation potential." Journal of Industrial Ecology. Submitted.

Burnham, A., Lu, Z., Wang, M., Elgowainy, A. "Regional emissions analysis of light-duty battery electric vehicles. Atmosphere." Submitted.

Lu, Z., Elgowainy, A. "Consumption-based regional electricity characteristics of North American electrical network." In preparation.

References

1. Liu, X., Elgowainy, A., Vijayagopal, R., Wang, M. (2021). "Well-to-wheels analysis of zero-emission plug-in battery electric vehicle technology for medium- and heavy-duty trucks." *Environ. Sci. Technol.*, 55, 538–546.

I.5 Transportation Energy Evolution Modeling (Oak Ridge National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $500,000	DOE share: $500,000	Non-DOE share: $0
Project Funding (FY20-FY21): $1,000,000	DOE share: $1,000,000	Non-DOE share: $0
Total Expected Project Funding: $1,500,000	DOE share: $1,500,000	Non-DOE share: $0

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 ongoing R&D. Technology impacts (e.g., energy consumption, consumer costs, and GHG emissions) 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 and scientists. Meanwhile, suppliers seek less risk and a good public image, in addition to profits. These factors, both individually and in combination, present challenges in understanding and modeling supplier behavior and consumer acceptance of advanced vehicle technologies.

To alleviate these challenges, the Transportation Energy Evolution Modeling (TEEM) program developed the MA3T (Market Acceptance of Advanced Automotive Technologies) model and its derivative models to simulate market penetration and dynamics in transitions toward energy efficient vehicle and mobility technologies. MA3T output is annual sales share of either a vehicle or mobility technology (e.g., 42-volt mild hybrid, 200-mile 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 IIASA, VTO EEMS, Hydrogen and Fuel Cell Technologies Office (HFTO), Bioenergy Technologies Office (BETO) and the Office of Energy Efficiency and Renewable Energy (EERE), for both adaption of MA3T for other purposes and application of it. The TEEM team has published over 90 peer-reviewed articles (https://teem.ornl.gov/publications.shtml), including 10 during FY 2021.

Objectives

The objectives of the TEEM 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 plug-in electric (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 2021 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 impacts of the expansion of charging infrastructure, different charging speeds, battery degradation, feedback from the used vehicle market and restriction on consumer choices.

Results

1. Climate and Health Benefits of Long-haul Electric Trucks

Invited by *Joule* to preview a designated article, the team published an article on climate and health impacts of long-haul electric trucks [1]. Published by *Environmental Science and Technology* and authored by Tong et al. [2], the previewed article monetized the health and climate damages at somewhere between a 47%–54% increase and a 77%–88% reduction. The preview article by the team argued for adjustments to the marginal emission and static assumptions. In fact, with the use of average emission factors and a simple weighting method to reflect transition dynamics, the impacts are found to be almost certainly positive, with a 7%–94% reduction in damages, as shown in Figure I.5.1. More detail on this can be found in the published article [2].

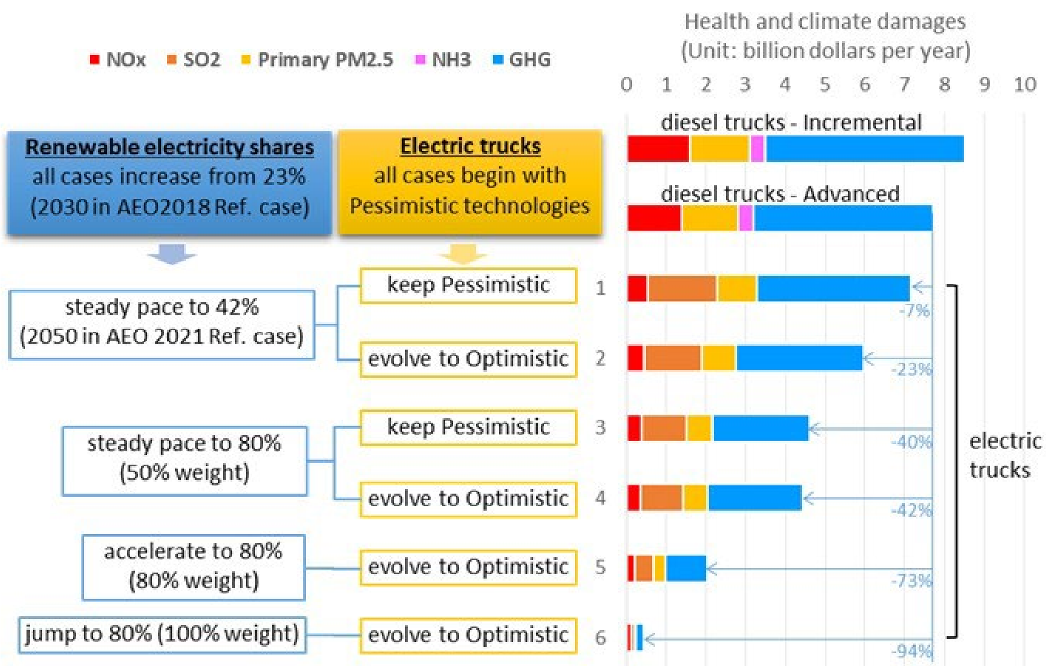

Figure I.5.1 Health and climate damages--diesel trucks vs electric trucks [1]. Source: ORNL

2. MA3T Improvements and Applications

Two major upgrades for MA3T are being carried out—modeling the used vehicle market and calculating consumer surplus.

Even with accelerated adoption of electric vehicles, petroleum consumption from the increasingly durable legacy gasoline vehicles could still pose a barrier to President Biden's 2050 net zero goal. Expanding MA3T to be able to consider the used vehicle market and its dynamics with the new vehicle market will allow analysis of policies that may aim at accelerating retirements of legacy gasoline vehicles from the vehicle fleet. Such policy goals can be controversial and should be informed by systematic model-based analysis that objectively anticipates the associated benefits and risks. Detailed vehicle registration data from 2002-2020 have been purchased from Information Handling Systems – IHS - Automotive and have been cleaned and merged with used vehicle price data from the Consumer Expenditure Survey. Vehicle scrappage schedules and price elasticities are being estimated for calibration of the MA3T-Used module in order to align it with the current new vehicle sales module of MA3T. The MA3T-Used module will "tell" the new vehicle sales module the costs and benefits of buying a used vehicle by fuel type, thereby "influencing" the choices among new vehicle purchases.

The calculation of consumer surplus, the second upgrade, enables MA3T to analyze the impacts of broader policies, such as incentives for used vehicle early retirements or replacement with EVs and banning of gasoline vehicles. The positive impacts of such policies are usually measured in terms of increased EV sales or reduced GHG emissions, but their negative impacts (e.g., restricting consumer choices) have often been ignored. Consumer surplus calculation is one method to capture negative impacts and to allow anticipation of market resistance. MA3T has been upgraded to calculate and output consumer surplus change, for example as a result of choice restriction. The upgraded MA3T is being used for a working paper on U.S. LDV net zero pathways.

3. Regional Electric Vehicle Infrastructure Strategic Evolution (REVISE) 2.0 Model

This task is to develop an open-source on-premises software for national electric vehicle infrastructure planning. The software, named REVISE 2.0, helps users to make infrastructure planning decisions based on different technology, policy, and traveler assumptions. The open-source code and the compiled software are published in GitHub (https://github.com/xiefei0117/REVISE-national-charging-infrastructure-model), and a paper on national infrastructure analysis using REVISE 2.0 was published in Applied Energy in FY 2021 [3]. Figure I.5.2 shows example EV charging infrastructure expansion strategies along U.S. interstate highways to support inter-city passenger travel demand between metropolitan areas.

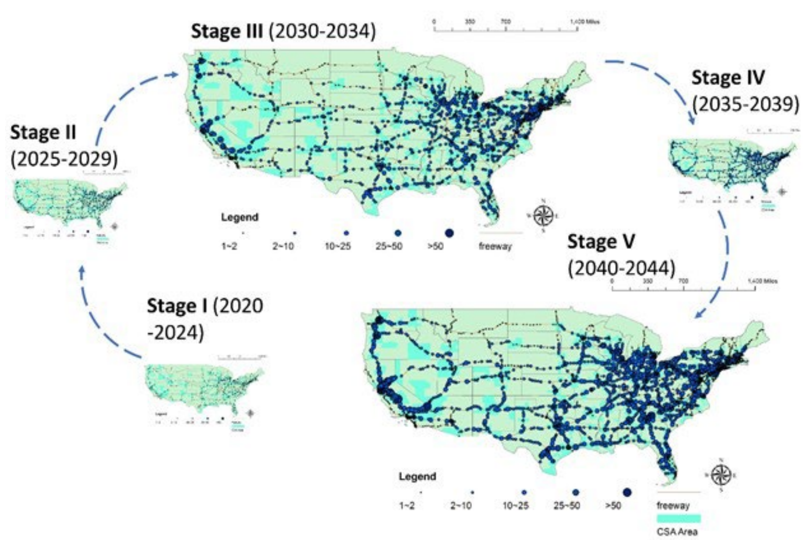

Figure I.5.2 Expansion of Charging Infrastructure Systems – Output from REVISE 2.0 with close-up display of results in two selected periods. Source: ORNL

4. Empirical Estimation of Route Length Along U.S. Interstate Highways Based on Great Circle Distance

This study was to develop simple linear regression models to estimate route distances along interstate highways in the U.S. based on great circle distances (GCDs). The motivation was that calculating routing distances is a necessary step for most transportation energy projects, though this requires non-trivial network processing efforts. Many projects only require approximated distances, which could be estimated based on the GCDs, and the GCDs are much easier to compute (it assumes the earth is a perfect sphere with a radius of 6378.137 km and calculates the sphere surface distance between two points of given longitude and latitudes). As part of this study, a database was created whereby users could query the appropriate empirical statistical regression models for selected regions. A paper that describes the methods and shows the database was published in Transportation Research Record [4]. Figure I.5.3 shows geographic variations of the slope coefficient in the state-level empirical statistical models of route distance estimation. The slope coefficient is expected to be higher than 1, indicating that the actual route distance is longer than the GCD. Larger slopes indicate that a longer route distance is expected for the same GCD.

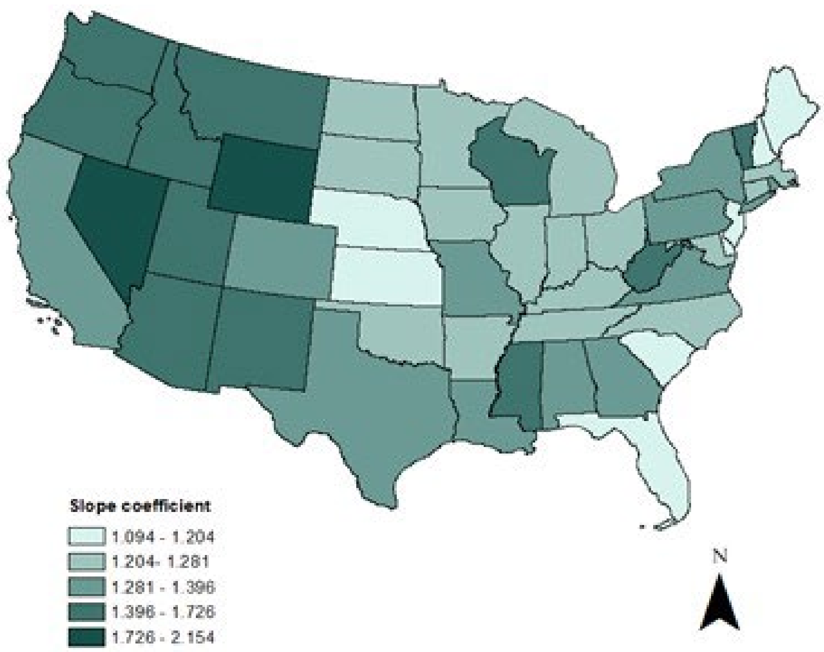

Figure I.5.3 state-level empirical statistical models of route distance estimation. Source: ORNL

5. Deployment Priority of Public Charging Speeds for Increasing Battery Electric Vehicle Usability

The impact of different charging speeds on BEV usability is conducted using trip-chain data from NHTS 2017 [5]. Figure I.5.4 shows a heatmap of daily expected driving range with different levels of charging power under four scenarios. Scenarios 1 is a theoretical and ideal case that no charging constraint exists. Although it is not realistic, this scenario gives an overall benchmark on the expected driving range of the 150-mile-range BEV. Scenario 2 added the constraint of battery capacity. Compared with scenario 1, the expected driving range decreases for all types of chargers. Scenario 3 is a case that considers the remaining battery capacity and trip chain constraints. It is the most realistic case and suggests that the expected daily driving range across direct current fast charger (DCFC), smart charging, and extreme fast charging do not significantly differ from each other. Scenario 4 is a special case of Scenario 3 in which BEVs only charge once daily, at the stop with the longest dwell time. In this case, the expected daily driving range drops further for all charger types and, for all but the level 2 charger type, is equivalent across charger type. As the sole exception, the level 2 charger has a slightly lower expected daily driving range.

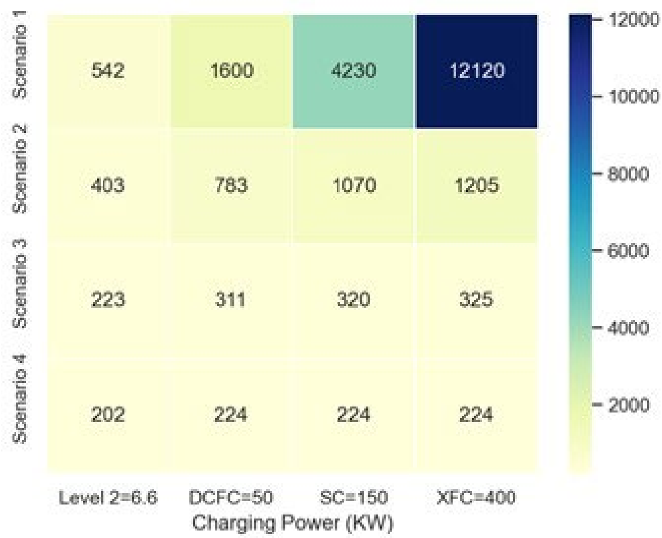

Figure I.5.4 Expected daily driving range, in miles, by charging speed (95th percentiles of the expected range distribution as the expected driving range). Source: ORNL

Conclusions

In FY 2021, the TEEM team conducted research on charging infrastructure, vehicle efficiency, consumer surplus, and vehicle technology-related topics that supported improvements of the MA3T model. The team also published studies on charging infrastructure, long-haul truck electrification and contributed to a National Academies study examining technologies that could improve LDV fuel economy [1]. 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

Burnham, Andrew, et al., 2022, "Comprehensive Total Cost of Ownership Quantification for Vehicles with Different Size Classes and Powertrains." No. ANL/ESD-21/4. Argonne National Lab. (ANL), Argonne, IL (United States).

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Lin, Zhenhong, Fei Xie, and Shiqi Ou, 2020, “Modeling the external effects of air taxis in reducing the energy consumption of road traffic.” Transportation Research Record 2674, No. 12: 176–187.

Liu, Nawei, Fei Xie, Zhenhong Lin, and Mingzhou Jin, 2021, “Empirical Estimation of Shortest Route Length Along U.S. Interstate Highways Based on Great Circle Distance.” Transportation Research Record 2675, 1248-1253, https://doi.org/10.1177/03611981211015251.

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5. Li, W. Lin, Z. (2021). Deployment Prioritization of Public Charging Infrastructure – Insights from Travel Behaviors and Traffic Patterns. In Proceedings of the 100th Annual Meeting of Transportation Research Board. Washington DC.

Acknowledgements

Other project team members are Stacy Davis, Janet Hopson, David Greene, Zulqarnain Khattak, Mingzhou Jin, Ben Leard, Wan Li, Nawei Liu, Mike Maness, Shawn Ou, Fei Xie.

I.6 Transportation Macroeconomic Accounting Models: VISION and Non-Light Duty Energy and Greenhouse Gas (GHG) Emissions Accounting Tool (NEAT) (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $400,000	DOE share: $400,000	Non-DOE share: $0
Project Funding (FY20-FY21): $650,000	DOE share: $650,000	Non-DOE share: $0
Total Expected Project Funding: $1,050,000	DOE share: $1,050,000	Non-DOE share: $0

Project Introduction

Energy use by the U.S. transportation sector has significant impacts on national energy security and emissions. To help research and develop technologies to reduce those impacts, VTO needs strong analytical modeling capabilities to compare and evaluate the fleet impact of vehicle and fuel technologies by employing consistent, systematic approaches and methodologies. The macroeconomic accounting models, VISION and NEAT ([1] and [2] respectively) have been previously developed to provide estimates of the potential energy use, oil use, and carbon emissions impacts of advanced LDVs, medium-duty vehicles, HDVs, and freight modes, as well as of alternative fuels, at the national level. VISION provides estimates of the potential energy use, oil use, and carbon emissions impacts of advanced light- and heavy-duty vehicle technologies and alternative fuels while NEAT focuses on the five domestic freight carrying modes and their use of alternative fuels. The five modes are: (1) Intercity Freight-carrying Trucks, (2) Freight Rail, (3) Domestic Freight Marine, (4) Domestic Freight Aviation, and (5) Pipeline.

This project 1) annually updates and calibrates the VISION/NEAT models with projections from the EIA's AEO Reference Case [3] and the Department of Transportation's Federal Highway Administration Freight Analysis Framework (FAF) [4], and 2) enhances the extant MDHD modeling capabilities and adds heterogeneity to the model by adding flexible inputs for new mobility patterns and demographic variation.

The annually updated and enhanced tools should better serve key stakeholders and provide the VTO Analysis Program with a systematic and consistent approach to evaluate emerging technologies and trends as well as the expanding the DOE MDHD R&D portfolio. Argonne is working with the National Renewable Energy Laboratory (NREL) on this task. DOE EERE programs and other agencies use these models extensively in projects such as other VTO analyses, SMART Mobility, H2@Scale, and Natural Gas analysis to evaluate the impacts of advanced vehicle/fuel technologies. The models are also widely used by researchers across universities, state agencies, consulting companies, and energy companies. VISION-online (https://vision.es.anl.gov/) is a web-based lite version, developed in FY 2019, of the VISION model. VISION-online allows both technical and non-technical users to run quick analyses of fleet impacts by changing key inputs including market penetration, annual VMT, and vehicle efficiency by technology and type. VISION-online also acts as an educational tool to help users understand major functionalities of the VISION model.

Objectives

The project objective is to develop and update macroeconomic accounting model capabilities for the VTO Analysis Program and other programs to systematically and consistently evaluate and/or compare vehicle technologies, freight modes, and fuel systems with regard to energy and environmental impacts. The VISION/NEAT models were, in fact, originally developed to serve this goal. Enhanced MDHD capabilities and model heterogeneity will both respond to the needs of the Transportation Decarbonization Analysis (formerly "Benefits Analysis") and reflect the expanding DOE R&D portfolio in the MDHD space. These enhancements will also reflect emerging trends, such as the growth in local and regional shipping relative to long haul, and will support the future incorporation of emerging technologies, such as shared vehicles, and connected and automated commercial vehicles.

In FY 2021, this project analyzed the impact of vehicle upsizing using VISION. The EIA's AEO estimates energy consumption in all sectors of the economy for the United States through 2050. However, historically, the market share estimated for light trucks has generally been lower than the actual number of sales, leading to energy projections that are overly optimistic. The specific objective has been to quantify the vehicle emissions and energy use assuming a different mix of cars and trucks and identify possible potential technical pathways available to mitigate some or all of this vehicle upsizing, including lightweighting, hybridization and electrification, and engine downsizing.

Approach

There are two tasks under this project. The following describes the method for each task separately. Figure I.6.1 shows the overall VISION/NEAT model framework, along with the vehicle technologies and transportation fuel pathways considered.

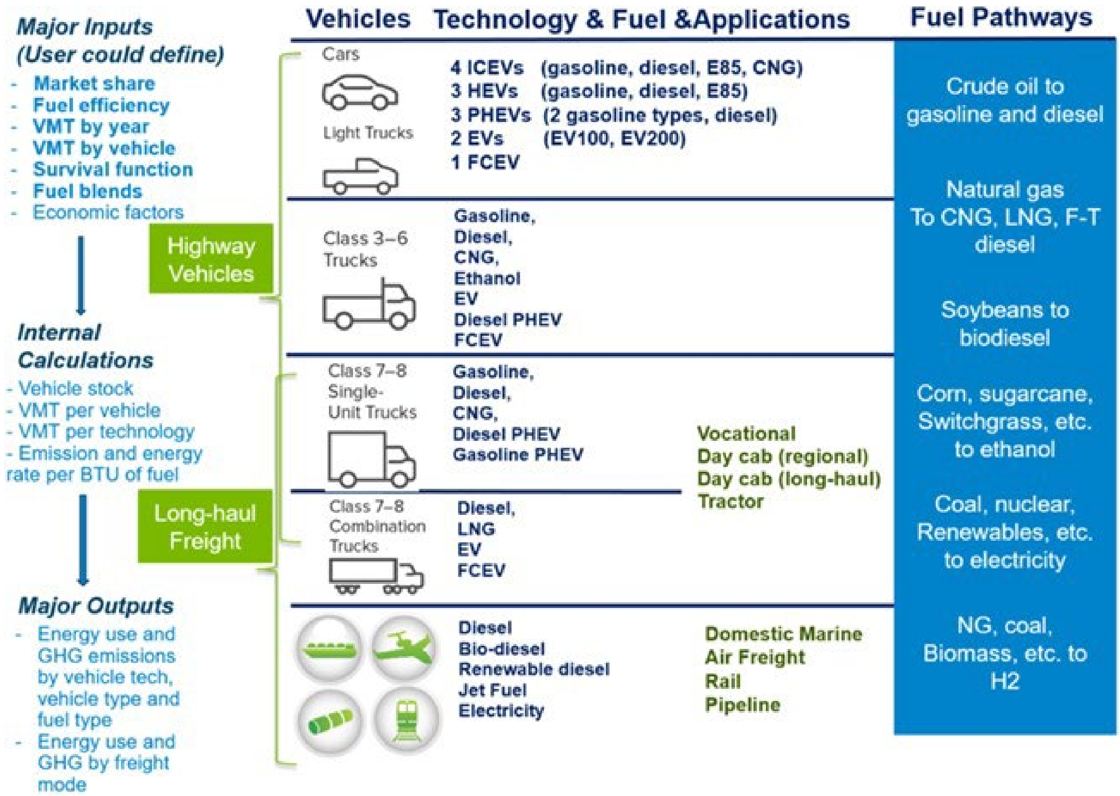

Figure I.6.1 VISION/NEAT Model Structure. Source: ANL

Task 1 Annual Update and Enhancement: VISION/NEAT were updated according to the latest annual data in order to align the base case with the reference cases of the current AEO and FAF projections. The models were also revised to reflect energy and emissions coefficients from the latest Argonne GREET model [5]. The models were calibrated to match the total energy consumption of highway vehicles and of the freight sector, by fuel type, with projections from the AEO. Historical numbers for market penetration, stock, freight mode shares, vehicle usage (e.g., annual miles and lifetime miles) and efficiency, survival by vehicle technology and vehicle class, as well as many other technological and regulatory factors were also updated using information from various data sources, including highway statistics, the Transportation Energy Data Book (TEDB) [6], the EIA projections to 2050 [7], the U.S. Census, Wards' Auto, and others. As in previous years, Argonne will release the models to the public on its website (more specifically, https://www.anl.gov/es/vision-model for VISION and https://www.anl.gov/es/neat-nonlight-duty-energy-and-ghg-emissions-accounting-tool for NEAT) and address users' questions as needed. Major inputs that can be changed by users of VISION and NEAT to define their own scenarios include, but are not limited to, the following:

VISION

- Market penetration by technology
- Fuel economy by technology
- Vehicle survival rate
- Alternative fuel energy and carbon emissions rate (per mile)
- Light truck share of the total LDV market
- Share of Fischer-Tropsch diesel/biodiesel in diesel (by volume)

- Electric generation mix
- Flex-fuel vehicle, VMT share
- Ethanol production share by feedstock
- Hydrogen production share by feedstock
- LDV VMT growth rate
- Diesel share in heavy-duty truck VMT
- Fuel price (i.e., in comparison to gasoline)
- Vehicle cost (in comparison to a conventional midsize car or light truck, in ratio).

NEAT

- Ton-mile change factors over 2010 values by commodity
- Ton-mile shares by mode within commodity
- Modal energy intensity/efficiency (i.e., Btu/ton-mile) by commodity
- Fuel shares (i.e., % of petroleum fuels, biofuels, electricity by volume) by mode
- Electricity generation primary fuel shares (% kWh/fuel).

This project enhances MDHD model capabilities to better align the model with emerging technologies and trends, the growing DOE MDHD R&D portfolio, and the MDHD components of the annual VTO Transportation Decarbonization Analysis. FY 2020 work focused on the HD module. The enhancement will be fully completed in FY 2022.

The MDHD stock in the previous VISION was segmented into three markets: Class 3–6, Class 7 and Class 8 Single Unit (SU), and Class 7 and Class 8 Combination trucks. Now the model has been enhanced to separate Class 7 and Class 8 into three market segments: vocational single-unit trucks, day cab (regional) tractor-trailer combination trucks, and sleeper (long haul) tractor-trailer combination trucks, with separate accounting for multiple powertrains. Table I.6.1 shows the twenty different powertrains that were considered, though not all powertrains will be included in each market segment. Selection of appropriate powertrains for each segment were made in consultation with the DOE and the VTO Transportation Decarbonization Analysis team.

Table I.6.1 Alternative Powertrains for Class 7-8 Trucks

	Class 7-8 Sleeper	Class 7-8 Day Cab	Class 7-8 Vocational
Diesel	Yes	Yes	Yes
Gasoline (incl flex)			Yes
CNG/LNG	Yes	Yes	Yes
HEV (Diesel)	Yes	Yes	Yes
HEV (Gasoline)			
BEV	Yes	Yes	Yes
PHEV (Diesel)	Yes	Yes	Yes
PHEV (Gasoline)			Yes
FCEV	Yes	Yes	Yes

Task 2 Impact of Vehicle Upsizing: The EIA's AEO 2020 estimates a lower share of light trucks in the future than many third-party forecasts. This analysis develops 20 different scenarios, changing the mix of cars, crossovers, SUVs, pickups, and vans from the AEO 2020 Reference Case, and calculates the average fuel economy in these alternate scenarios with larger (or smaller) vehicles.

The VISION model estimates energy consumption and emissions for vehicles through 2100 given vehicle fuel economy and sales mix, accounting for typical travel patterns and vehicle scrappage rates [1]. VISION splits vehicles into the two regulatory size classes and offers 14 different combinations of vehicle powertrains and fuel types for each. For each model year, we determine the sales-weighted average fuel economy for our AEO-modeled vehicles with our updated fleet sales mix to use as inputs into VISION. This analysis uses VISION defaults to quantify the scrappage of these vehicles over time. VMT distributions for cars and light trucks have historically differed, with light trucks driving more than cars [8], [9]. Additionally, VISION includes an elasticity for VMT based on the price of fuel. This analysis does not consider changes in mobility along with changes in size class, but rather makes a proportional adjustment to VMT to match total light-duty vehicle travel in each year. This analysis normalizes VMT, redistributing VMT across the vehicle fleet but not changing the total amount of travel.

Quantifying the energy and emissions for each vehicle type requires a full cradle-to-grave analysis including both the fuel consumption cycle and vehicle manufacturing cycle. This analysis uses the GREET model to estimate the embodied (or "well-to-wheel") energy consumption and emissions for each vehicle type [5] using default values for electricity emissions (matching AEO 2020) and for upstream gasoline emissions. We account for the vehicle powertrain, size class, and total weight when estimating lifecycle energy consumption for these vehicles.

This analysis considers four different mitigation strategies to improve fuel economy in spite of vehicle upsizing: vehicle lightweighting, hybridization of ICE engines, full electrification of ICE vehicles, and reduced ICE horsepower. For lightweighting and mild hybridization, we adjust the fuel economy of each vehicle based on the technology matrix published by EIA in the AEO documentation [3]. For powertrain switching, we estimate the fraction of the ICE fleet that must be converted to either HEV or BEV to achieve the total energy consumption as calculated by VISION [1]. Finally, for decreased performance, we note that engine performance and efficiency can be viewed as a tradeoff [10] [11], and estimate the gain in fuel economy from reduced horsepower [12]. For each strategy we consider cumulative energy use and GHG emissions through 2050.

Results

The VISION 2021 base case reflects projections relating to light and heavy highway vehicles in EIA's AEO 2021. In Figure I.6.2, this can be seen by the slight re-adjustment of the trend lines in the following year. In the 2021 VISION model update, these projections have been extended to the year 2100. For GHG emissions, the VISION model uses carbon coefficients derived from Argonne's GREET model. GREET GHG coefficients account for the full fuel cycle. VISION 2021 has been updated to reflect the (1) EIA AEO 2021 Reference Case, and (2) GHG and upstream energy rates from GREET1_2020. Class 7–8 heavy-duty vehicles now are subdivided into three market segments with separate accounting for multiple powertrains technologies: vocational single-unit trucks, day cab (regional) tractor-trailer combination trucks, and sleeper (long haul) tractor-trailer combination trucks.

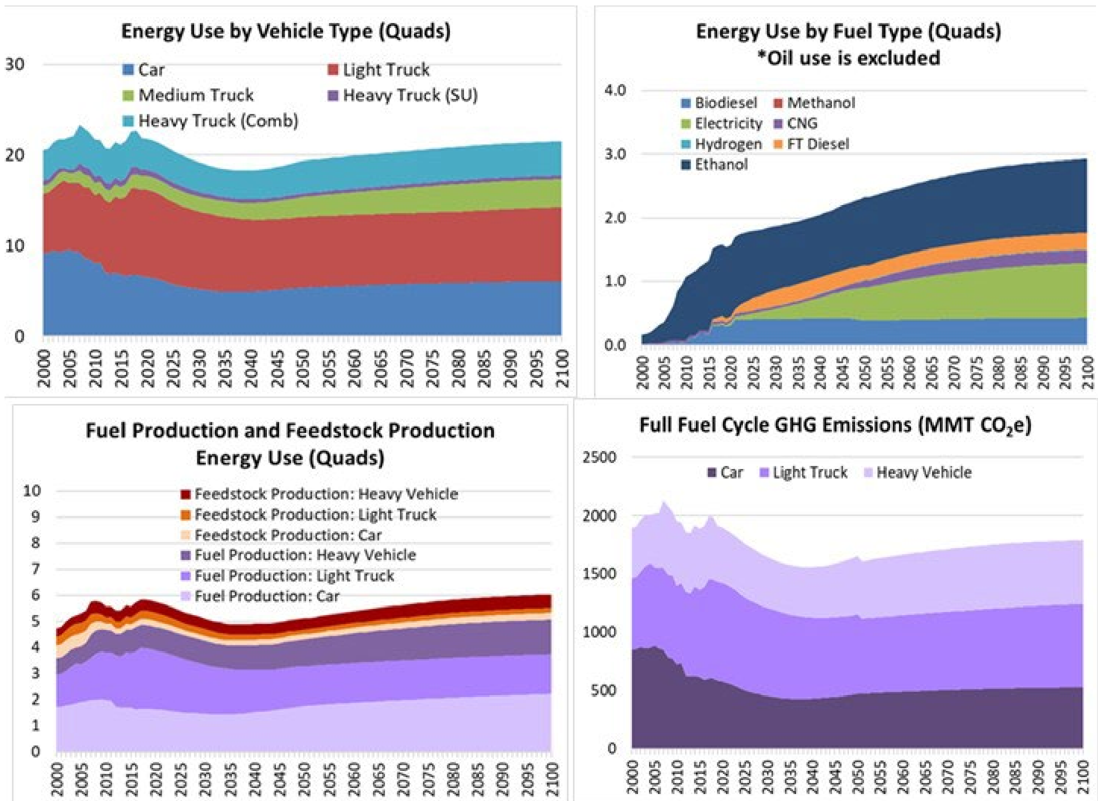

Figure I.6.2 VISION 2021 Base Case, Full-fuel cycle energy use and GHG emissions by fuel and vehicle type. Source: ANL

This task involves quantifying the total energy consumption and lifecycle GHG emissions for LDV nationwide through 2050 for each of the scenarios defined. In the AEO Reference Case, annual LDV petroleum consumption, energy use, and GHG emissions drop by around 15% from 2020 to 2030. Table I.6.2 shows the total energy and GHG emissions, via percentage change from the AEO 2020 Reference Case, for each of the twenty scenarios through 2050, along with the national costs based on the same format.

In general, each technology pathway considered for mitigation yields similar results in all scenarios. Specifically, this analysis finds that, by 2050, on average:

- A 20% mass reduction lowers GHG emissions by about 1% while increasing total consumer costs by about 3%;
- Micro-hybrid ICEs, with engine stop-start technology, lower GHG emissions by just over 1% while slightly decreasing total consumer costs;
- Mild-hybrid ICEs, where the battery can assist propulsion of the combustion engine, lower GHG emissions by about 2% while increasing total consumer costs by about 2%;
- A 50% share of full HEVs lowers GHG emissions by about 9% while decreasing total consumer costs by about 0.5%;
- A 50% share of full BEVs lowers GHG emissions by over 12%, but increases total consumer costs by about 6%; and
- A 15% reduction in engine horsepower lowers GHG emissions by about 2.5% and decreases total consumer costs by about 1%.

Table I.6.2 Percentage Change of Each Metric Relative to AEO 2020 Reference Case

Scenario	Energy				GHG Emissions		Costs
	Petroleum	Biofuels	Electricity	Total	Fuel	Lifecycle	National
Baseline: AEO 2020	2,780 billion gallons	329 billion gallons	2,315 TWh	439 quad	33,619 million metric tons CO_2-eq	37,254 million metric tons CO_2-eq	$26.5 trillion
#1	19%	19%	-45%	18%	17%	18%	5%
#2	10%	10%	-44%	10%	9%	10%	-5%
#3	17%	17%	-45%	15%	15%	15%	23%
#4	1%	1%	-11%	1%	1%	1%	-1%
#5	-12%	-12%	45%	-11%	-11%	-11%	-4%
#6	17%	17%	-45%	16%	16%	16%	18%
#7	11%	11%	-32%	10%	10%	10%	9%
#8	13%	14%	-36%	12%	12%	12%	14%
#9	11%	11%	-30%	10%	10%	10%	11%
#10	7%	7%	-21%	6%	6%	6%	5%
#11	5%	5%	-18%	4%	4%	4%	0%
#12	8%	8%	-19%	7%	7%	7%	9%
#13	5%	5%	-14%	5%	5%	5%	5%
#14	6%	6%	-10%	5%	5%	5%	8%
#15	3%	3%	-4%	2%	2%	2%	4%
#16	-1%	-1%	3%	0%	0%	0%	-1%
#17	-2%	-2%	13%	-2%	-2%	-2%	0%
#18	-6%	-6%	25%	-5%	-5%	-5%	-2%
#19	2%	2%	-10%	2%	2%	2%	1%
#20	2%	3%	6%	3%	3%	3%	7%

Conclusions

The VISION/NEAT models have been used in several DOE EERE programs and activities such as the VTO analysis program, Transportation Decarbonization (formerly "Benefits") Analysis, SMART Mobility, and H2@Scale, in order to evaluate the impacts of advanced vehicle technologies. VISION/NEAT has over 4000 users.

In this project, Argonne's VISION/NEAT model was fully updated to match the projections in the EIA AEO 2021 Reference Case and FAF4.0. VISION/NEAT is now also updated with GHG and upstream energy rates from GREET1_2020. Historical vehicle sales, stock, fuel economy, and other information were collected and documented in the model. The MDHD module is further segmented into Class 7 and 8 Vocational, Day Cab, and Sleepers, with projections aligned with the AEO 2021 Reference Case.

A vehicle upsizing scenario analysis shows that energy consumed by on-road light-duty vehicles in the U.S. can vary by as much as 10% by changing assumptions regarding the mix of sedans, utility vehicles, vans, and pickup trucks. Scenarios that are aligned with third-party forecasts of vehicle sales assume a greater proportion of light trucks and fewer cars, which yields petroleum consumption 3%–8% higher than the Reference Case in the 2020 AEO. This results in GHG emissions that are 5%–7% higher and a 4%–9% increase in consumer spending on vehicles and fuel. This incremental energy consumption can be offset by considering additional technologies for these vehicles; electrification, hybridization, reduced engine power, and lightweighting can all mitigate increases in vehicle size to some extent. If sedans were fully phased out in favor of sport utility vehicles, a sales share of either 30% battery electric vehicles or 39% hybrid electric vehicles would be sufficient to return to the GHG emissions baseline as set by the AEO Reference Case.

Key Publications

David Gohlke, Jarod Kelly, Thomas Stephens, Xinyi Wu and Yan Zhou, 2022, "Mitigation of Emissions and Energy Consumption Due to Light-Duty Vehicle Size Increases." presentation accepted for the 2022 Transportation Research Board Annual Meeting.

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Acknowledgements

The U.S. Department of Energy through the Vehicle Technologies Office supported this work. The authors thank Jacob Ward and Raphael Isaac for their continued support of this project and their useful and constructive comments.

I.7 Transportation Energy Data Book and Fact of the Week (Oak Ridge National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding: $400,000	DOE share: $400,000	Non-DOE share: $0
Project Funding (FY20-FY21): $800,000	DOE share: $800,000	Non-DOE share: $0
Total Expected Project Funding: $1,200,000	DOE share: $1,200,000	Non-DOE share: $0

Project Introduction

To inform stakeholders, transportation analysts and VTO staff require quality current and historical data and information on the transportation sector. The TEDB 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 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. Meanwhile, stakeholders, academia and others use these data to help move the United States toward using less petroleum and reducing greenhouse gas emissions.

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 TEDB website twice a year as Editions 39.1 and 39.2, and (3) produced a draft of Edition 40 of the TEDB, including updated data and information.

Approach

Oak Ridge National Laboratory's (ORNL's) approach for the TDP can be categorized into four stages: discovery, due diligence, approval, and publication as shown in Figure I.7.1. Data are discovered from a myriad of public and private sources, and ORNL performs due diligence to ensure that the data are defined and notated correctly. In this stage of the approach, ORNL works with other laboratories (e.g., Argonne and NREL), 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 that data derived from differing sources are comparable. Explanatory text is written, and tabulations/graphics are generated in Microsoft (MS) Word and/or MS Excel. DOE reviews and approves each FOTW and the tabulations/graphics in the TEDB before final publication. The FOTW is published on the VTO Transportation Fact of the Week webpage (https://energy.gov/eere/vehicles/transportation-fact-week), and an email with the FOTW is sent (via the GovDelivery system) to the subscription list every week, typically on Monday afternoons. The PDF and MS Excel files for the TEDB (https://tedb.ornl.gov/) are posted on the website hosted by ORNL. The major topics for the TDP publications are provided in Table I.7.1.

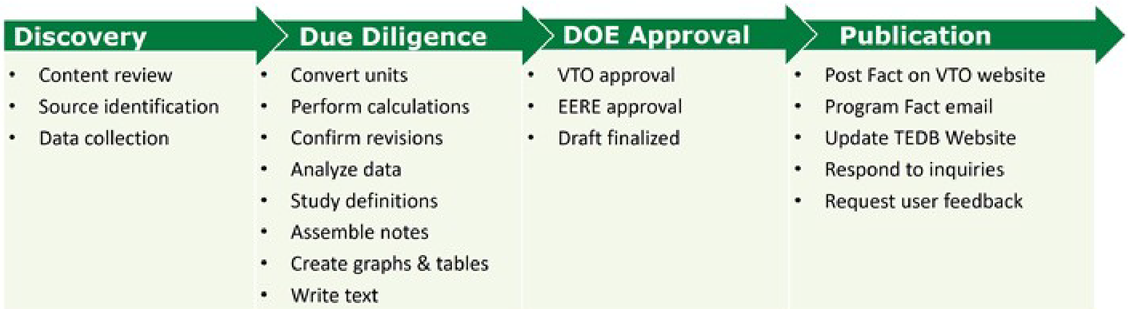

Figure I.7.1 Approach for the transportation data program at ORNL. Source: ORNL

Table I.7.1 Major Topics for the Transportation Data Program at Oak Ridge National Laboratory

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

Results

The weekly email for the FOTW began on July 27, 2015, with 50 email subscribers. As of the end of FY 2021, there were 25,371 subscribers to the Transportation FOTW newsletter.

FOTW 1154 through 1205 were posted on the VTO website during FY 2021 as listed in Table I.7.2. For FY 2021, FOTW content accounted for 336,360 pageviews, or 50% of all VTO website pageviews during the FY. Of those pageviews, 304,605 were unique visits, meaning that some visitors (31,755) to FOTW content were repeat visitors. Of all VTO website visits, 58% (294,799) entered the VTO website through a FOTW landing page. Fact 915, Average Historical Annual Gasoline Pump Price from 1929- 2015, had the highest number of pageviews of any VTO website page—196,584, or 29% of all website pageviews during the FY.

Table I.7.2 Facts of the Week Posted on the VTO website in FY 2021

Date Posted	Fact	Fact Title
09/27/2021	1205	Fourteen Different Models of Plug-in Electric Small SUVs Were Available in MY 2021
09/20/2021	1204	Fuel Wasted Due to U.S. Traffic Congestion in 2020 Cut in Half from 2020 to 2020
09/13/2021	1203	Light-Duty PEV Displaced 500 Million Gallons of Gasoline in the U.S. in 2020
09/06/2021	1202	U.S. Light-Duty Electric Vehicle Miles Traveled Reached 13.7 Billion Miles in 2020
08/30/2021	1201	11 Gasoline Powered Light-Duty Vehicle Models Achieved 50 MPG or Higher in 2021

08/23/2021	1200	Sales of New EV Were Up for 2020 While Conventional Vehicle Sales Were Down
08/16/2021	1199	U.S. Monthly Gasoline Price Has Averaged $2–$3 per Gallon Since December 2014
08/09/2021	1198	Average Age of U.S. Light-Duty Vehicles Reached a New High of 12.1 Years in 2020
08/02/2021	1197	Petroleum Use by U.S. Transportation Sector Declined to 12 MMBD in 2020
07/26/2021	1196	MY 2025 Class 4 Delivery Trucks Have Lowest Total Cost of Driving
07/19/2021	1195	The Small SUV Segment Has the Greatest Improvement in Fuel Economy of All LDV
07/12/2021	1194	For-Hire Freight Volume Was Not Impacted as Severely Passenger Volume
07/05/2021	1193	Nearly 76 GWh of Battery Cell Capacity Produced for U.S. PEV Market 2010 – 2020
06/28/2021	1192	Most U.S. PEV Battery Cells and Packs Produced Domestically 2018 –2020
06/21/2021	1191	Fourteen States Considering Zero-Emission Light-Duty Sales Requirements
06/14/2021	1190	Battery-Electric Vehicles Have Lower Scheduled Maintenance Costs than Other LDV
06/07/2021	1189	U.S. Net Petroleum Imports Negative for 2020
05/31/2021	1188	Consumers Can Estimate Upstream Greenhouse Gas Emissions for PEV
05/24/2021	1187	The Share of U.S. Workers Who Work from Home Grew from 20% to 71% in 2020
05/17/2021	1186	The Cost of Fuel for an Electric Vehicle is about 60% Less than for a Gasoline Vehicle
05/10/2021	1185	Nearly 1/3 of All Light Trucks Produced in MY 2020 had 9- 10-speed Transmissions
05/03/2021	1184	Half of all States Now Have at Least 1,000 Non-residential EV Charging Units
04/26/2021	1183	New Cars Purchased with Low Fuel Economy Ratings Assessed a Gas Guzzler Tax
04/19/2021	1182	Nearly 50 Light-Duty Plug-In Electric Vehicle Models Were Available in MY 2020
04/12/2021	1181	Gross Domestic Product and Vehicle Miles Traveled Declined in 2020
04/05/2021	1180	U.S. Vehicle Miles Traveled in April 2020 Was 40% Below April 2020
03/29/2021	1179	All-Electric Vehicles Have the Lowest Estimated Annual Fuel Cost
03/22/2021	1178	Gasoline Direct Injection was Installed on 55% of all LDV Produced in 2020
03/15/2021	1177	Fuel Economy of New Light-Duty Vehicles Reached a Record High MPG in 2020
03/08/2021	1176	The Average Household Spent 3.27% of its Income on Vehicle Fuel in 2018
03/01/2021	1175	Vehicles Registered in the District of Columbia Averaged 22 Miles per Gallon in 2018
02/22/2021	1174	Over 20,000 New Electric Vehicle Charging Outlets Were Installed in the U.S. in 2020
02/15/2021	1173	California Had the Highest Number of PEV Registrations per 1,000 People in 2018
02/8/2021	1172	New Light-Duty Vehicle Sales Declined by 15% from 2020 to 2020
02/01/2021	1171	Crude Oil Feedstock is the Dominant Cost Component in the Retail Price of Gasoline
01/25/2021	1170	Retail Gasoline Prices Ranged from $2.26/gallon in Mississippi to $3.67 in Hawaii
01/18/2021	1169	Vermont Had the Highest Number of Public Electric Vehicle Chargers per Capita
01/11/2021	1168	New Light Truck Price in 2020 was 43% Higher than the Average New Car Price
01/04/2021	1167	Median Driving Range of All-Electric Vehicles Tops 250 Miles for Model Year 2020
12/28/2020	1166	MY 2020 Light-Duty Vehicles Offered Consumers a Range of Fuel Economy Choices
12/21/2020	1165	When Adjusted for Inflation, the Price of Gasoline in 2020 was Similar to 1929
12/14/2020	1164	The Effect of Cold Temperatures on Fuel Economy
12/07/2020	1163	Average Retail Vehicle Fuel Prices, 2020
11/30/2020	1162	Shared Micromobility Replacing Car Trips
11/23/2020	1161	A Tool is Available for Estimating Charging Loads from Plug-In Electric Vehicles
11/16/2020	1160	Scooter Trips from Rental Services Averaged One Mile per Trip in 2020
11/09/2020	1159	Shared Micromobility Trips Grew by 62% in 2020
11/02/2020	1158	Transportation Fuels Were 62% of U.S. Government Energy Consumption in 2020
10/26/2020	1157	Per Capita Transportation Sector Energy Consumption Has Been Flat Since 1974

10/19/2020	1156	Texas has the Highest Speed Limit for Light-Duty Vehicles
10/12/2020	1155	Light-Duty Vehicles Use More Gas at Speeds Above 50 Miles per Hour
10/05/2020	1154	Class 3-8 Diesel Vehicle Population Is Becoming Cleaner in NO_x and Particulate Matter Emissions

The TEDB is an online publication that is published once per year with two mid-year updates to the tables and graphics. Although the draft of Edition 39 was delivered in fiscal year 2020, the final Edition 39 was approved by DOE and put online in January 2021. The April update to Edition 39 debuted online at the end of April 2021, with 77 tables and 9 figures updated with more recent data than was published in the original Edition 39. In August 2021, another 44 tables and 9 figures were updated. The draft of Edition 40 was completed and delivered on September 30, 2021, with a total of 223 tables and 71 figures of transportation data, many with historical series going back to 1970. The two appendices contain an additional 39 tables. Edition 40 will be posted to the website once DOE has reviewed and approved the content.

The TEDB website has a keyword search feature to help users find the data that they need quickly and efficiently in both PDF and MS 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 contact link so that users can easily contact the project principal investigator, Stacy Davis. The five highlights are changed three times each year, alongside the release of each TEDB update on the website. Other pages on the website provide access to an archive of older reports, citation information, and project contact information. The TEDB website had 48,372 pageviews in FY 2021. Google Scholar reports 4,110 citations for the TEDB as of October 2021.

Twice each month a graph from data in the TEDB and a sentence about the graph was provided to the NREL for the Clean Cities Coordinator's Newsletters.

Data collected in the TDP have also provided input to other VTO programs and other agency models, such as MA3T, GREET®, ADOPT, the Transportation Decarbonization Analysis, the U.S. Energy Information Administration's National Energy Modeling System, and the U.S. Environmental Protection Agency's Motor Vehicle Emission Simulator model.

Conclusions

TDP has facilitated successful publication in the form of weekly, monthly, and annual milestones delivered on time and within budget, with improvements over time. Having such accessible information leads to analyses that support program planning and evaluation and technology research to address transportation efficiency, which will help meet DOE's R&D priorities of reducing petroleum dependence and greenhouse gas emissions.

Key Publications

Davis, S. and R. Boundy (2021). "Transportation Energy Data Book: Edition 40." Oak Ridge National Laboratory, Oak Ridge, Tennessee. [Draft completed in FY 2021. To be published in final form in FY 2022.]

References

1. Davis, S. and R. Boundy (2021). "Transportation Energy Data Book: Edition 39." ORNL/TM-2020/1770, Oak Ridge National Laboratory, Oak Ridge, Tennessee.

I.8 Vehicle Choice Modeling and Benefits/Transportation Decarbonization Analysis (National Renewable Energy Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding: $600,000	DOE share: $600,000	Non-DOE share: $0
Project Funding (FY20-FY21): $1,200,000	DOE share: $1,200,000	Non-DOE share: $0
Total Expected Project Funding: $1,800,000	DOE share: $1,800,000	Non-DOE share: $0

Project Introduction

The U.S. Department of Energy's VTO and HFTO support R&D of affordable, efficient, and clean transportation options that will ensure fuel diversification, improve energy efficiency, and eventually achieve net-zero emissions. The programs include research on batteries, electric drive technologies, combustion, materials, fuel cells, and hydrogen storage. The intent of this project has been to develop tools and, using these tools, conduct analyses to estimate the benefits from DOE investments in these technology areas. Going forward the project will increasingly focus on pathways to achieving national transportation decarbonization goals through leveraging technologies supported by the VTO, HFTO and BETO.

Objectives

The work summarized in this progress report focuses on the project's objective to estimate the level of energy and emissions benefits from achieving VTO and HFTO program technical goals under an assumed continuation of historical policy conditions (i.e., based on policy conditions and technology goals from 2020). Work is ongoing to assess updated technology progress assumptions within alternative policy and economic contexts conducive to decarbonizing the transportation sector. The updated analyses will be documented in future reports.

Overall Approach

This evaluation includes deep dive analyses into the benefits of technology improvements on the U.S. LDV fleet and, separately, on the U.S. MDHDV fleet. This report summarizes the outcomes from each of these analyses both independently and in combination. Both analyses assume that technology improvements achieved 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 which might in the near future. As such, the impact of rolling out greater technology improvements into new vehicle sales starts, in these analyses, in 2025. Additionally, while the analyses do not quantify the benefits after 2050, the trends suggest that benefits will continue to grow.

Light-Duty Vehicle Approach

The benefits estimation for LDV is performed using the Automotive Deployment Options Projection Tool (ADOPT). ADOPT is a vehicle choice and stock model that estimates vehicle technology improvement impacts on sales, energy, and emissions [1]. It includes all the existing vehicle options for realism, 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.

VTO and HFTO program technical goals feed into ADOPT and are applied to the vehicles through time. The differing assumption sets are represented by a No Program scenario that reflects the technology improvements assumed to occur without contributions from 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 consumer price. Detailed technology improvement assumptions can be found in the full benefits assessment report listed in the Key Publications section.

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, which include expanding HEV sales and 2% plug-in electric (PEV) sales. These can be seen in the No Program scenario sales results, in Figure I.8.1. The simulation additionally matches the historic sales observations that indicate relatively higher priced and higher performance BEVs selling best to high-income households. Even under the No Program scenario, the costs and performance of advanced component technologies such as vehicle batteries are anticipated to improve, which results in changing sales trends into the future. Just before 2030 sales shift to greater expansion of HEVs until 2035, after which sales transition to expanding PHEV market share.

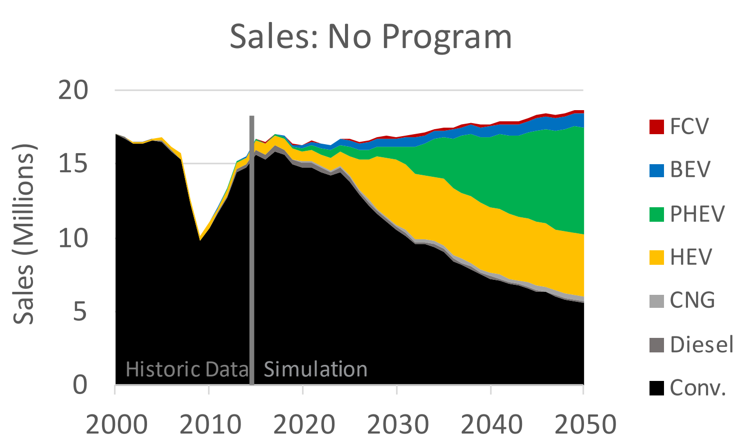

Figure I.8.1 No Program vehicle sales by powertrain. Source: NREL

The No Program scenario results in petroleum consumption dropping from 8 million barrels per day in 2020 to 5 million barrels per day by 2050. Carbon emissions drop from 1,365 to 924 million metric tons.

Next, the team evaluated the Program Success scenario, in which all the VTO and HFTO program goals are achieved simultaneously. While sales trends start similarly, with HEVs expanding and then PHEVs, sales under the Program Success scenario shift again to BEVs around 2040, as shown in Figure I.8.2. By 2050, this scenario results in 11% less annual petroleum consumption and 10% less annual carbon emissions than the No Program scenario.

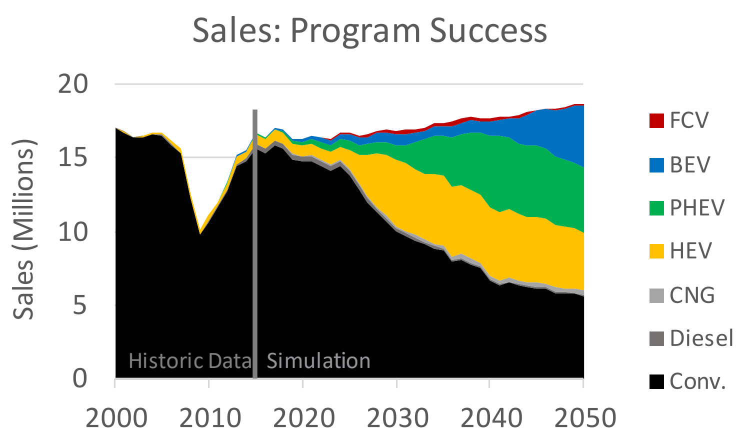

Figure I.8.2. Program Success vehicle sales by powertrain. Source: NREL

Heavy-Duty Approach

VTO and HFTO program benefits for Class 4-8 MDHD vehicles are estimated using a set of legacy modeling tools. This tool set includes the Future Automotive Systems Technology Simulator (FASTSim) vehicle powertrain model [2], the TRUCK payback-based market adoption model, and the heavy-duty stock (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., miles per gallon), adoption rates, and future in-use fleet energy consumption and emissions.

The SuperTruck initiative represents a key ongoing VTO investment in improving the energy efficiency of commercial vehicles, with SuperTruck II goals to increase diesel engine efficiency and long-haul tractor vehicle-level freight efficiency by 2021. In addition, VTO supports the 21st Century Truck Partnership (21CTP), a government/industry research collaboration that has established high-level goals for heavy vehicles and engines and is in the process of developing targets for electrification technologies for commercial vehicles across the MDHD spectrum. HFTO recently completed a first target-setting analysis for Class 8 long-haul tractors [3]. These goals, in addition to recent analysis by NREL for VTO, are used to establish future vehicle characteristics as inputs to FASTSim, the outputs from which then feed into TRUCK, which in turn provides inputs for HDStock. As with the light-duty analysis, technologies incorporating research goals are assumed to enter the market five years after the advancements are achieved with a 1.5 cost multiplier to convert manufacturing costs to consumer price. Detailed technology improvement assumptions can again be found in the full benefits assessment report listed in the Key Publications section below. The full MDHD results details can be found in the same report, and these are briefly summarized in the following section.

Heavy-Duty Results

The Program Success results represent realization of the 2020 program goals noted just above and are compared to a No Program Case derived from the comparable AEO Reference Case by removing future adoption of advanced diesel technologies supported by VTO or HFTO R&D from this Reference Case. The No Program Case retains the very small penetration of alternative powertrains from the AEO Reference Case, including plug-in diesel and gasoline hybrid EVs, BEVs, and FCEVs. The projections for each of these powertrains is below 0.6% of sales within each vehicle class and, when combined, account for less than 1.7%

of sales within any vehicle class. There is no market penetration of strong hybrids in either the AEO Reference or No Program Cases.

In the Program Success Case, advanced diesel and hybrid vehicles are very successful. These vehicles occupy a steadily increasing share of the diesel compression ignition (CI) segment into the future, and by 2040 achieve 97% of the new vehicle market for sleeper tractors, around 70% for day cab tractors and Class 7 and 8 vocational trucks, and 80% for Class 4-6 diesel vocational trucks. While the fuel economy of new diesel-powered trucks continues to improve through 2050, shares of alternative powertrains begin to supplant these technologies after 2040. By 2050, PHEVs, BEVs, and FCEVs combined account for more than 40% of the market in the analyzed classes, as shown in Figure I.8.3 and Figure I.8.4. This results in 28% less diesel consumption and 21% less GHG emissions annually in 2050, as shown in Figure I.8.5.

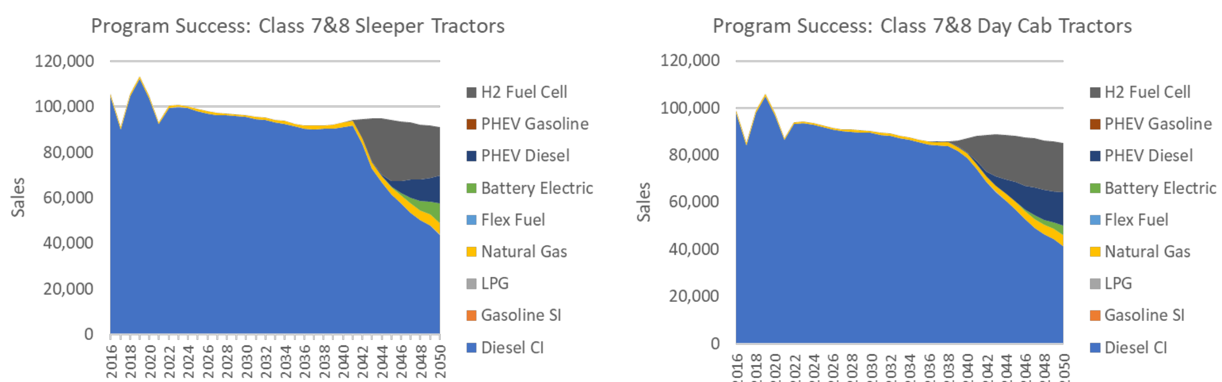

Figure I.8.3. Program Success Case tractor sales by powertrain. Source: NREL

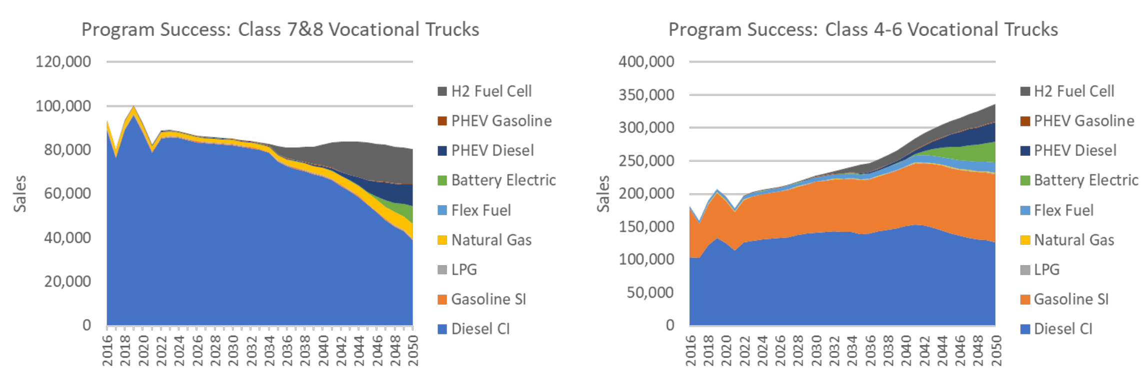

Figure I.8.4. Program Success Case vocational truck sales by powertrain. Source: NREL

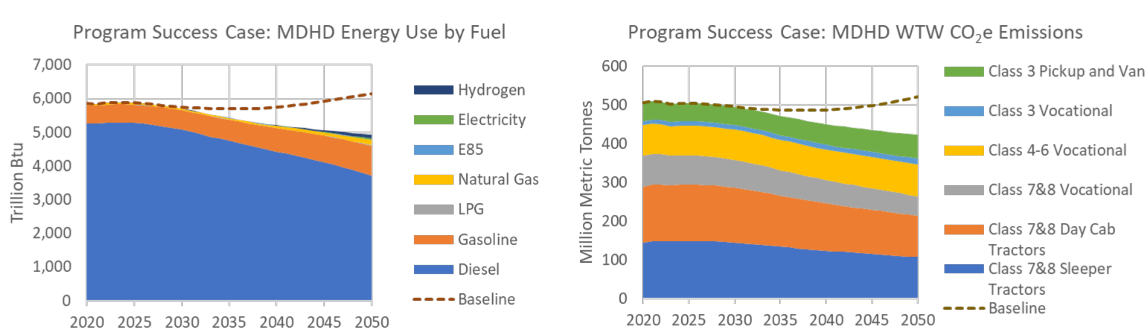

Figure I.8.5. Program Success Case MDHD fuel consumption and carbon emissions. Source: NREL

Conclusions

The results for the combination of light-duty and MDHD program success can be seen in Figure I.8.6. By 2050, annual petroleum consumption is reduced 15% and annual emissions 13%. The cases analyzed here are based on technology progress assumptions established in 2020 and do not account for potential future policies that may drive a more rapid transition to zero-emission vehicles. Future project updates will address updated assumptions within alternative policy and economic contexts conducive to decarbonizing the transportation sector.

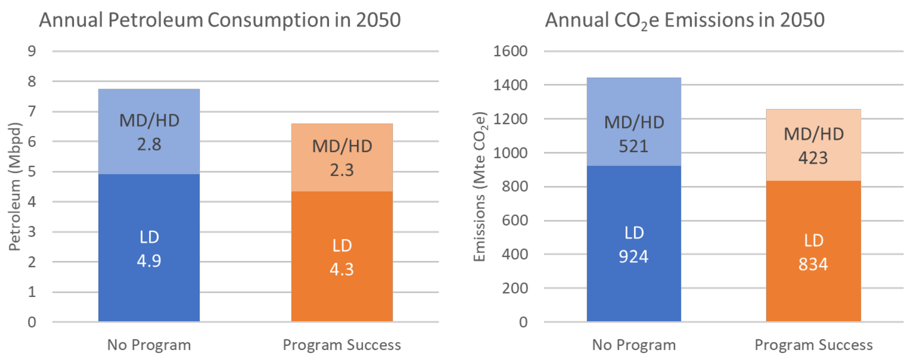

Figure I.8.6. Program Success Case MDHD fuel consumption and carbon emissions. Source: NREL

Key Publications

Aaron Brooker, Alicia Birky, Evan Reznicek, Jeff Gonder, Chad Hunter, Jason Lustbader, Chen Zhang, Lauren Sittler, Arthur Yip, Fan Yang, Dong-Yeon Lee. 2021. "Vehicle Technologies and Hydrogen and Fuel Cells Technologies Research and Development Programs Benefits Assessment Report for 2020," National Renewable Energy Laboratory Technical Report. NREL/TP-5400-79617. https://dx.doi.org/10.2172/1818458.

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2. 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.

3. Marcinkoski, J., "Hydrogen Class 8 Long Haul Truck Targets," Hydrogen Fuel Cell Technology Office Program Record # 19006, 2019.

Acknowledgements

Thank you to the U.S. Department of Energy's VTO and HFTO for their program and technical support. Specifically, thanks to thank Jacob Ward, Madhur Boloor, and Raphael Isaac of VTO and Neha Rustagi, Sunita Satyapal, and Marc Melaina of HFTO for their program support, technical guidance, and coordination with technology managers. Thanks to Sarah Kleinbaum, David Gotthold, Felix Wu and the U.S. Council for Automotive Research Materials Tech Team for input and feedback on integrating lightweighting and providing goals. Thanks to Gurpreet Singh, Ken Howden, Kevin Stork, Michael Weismiller, and Siddiq Khan for input on advanced combustion and fuels. Thanks to Brian Cunningham, Samm Gillard, and Susan Rogers for input on electrification. Thanks to Ned Stetson, Dimitrios Papageorgopoulos, Jesse Adams, and Greg Kleen for input on hydrogen fuel cell and storage technologies.

I.9 Utilizing Location History Data to Develop Travel Demand Prediction Models (National Renewable Energy Laboratory)

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Start Date: July 1, 2020 | End Date: June 30, 2021
Project Funding (FY20): $130,000 | DOE share: $130,000 | Non-DOE share: $0

Project Introduction

Recent advancements in predictive analytics, coupled with non-traditional data sources, can pave the way to next generation travel models that are as accurate as traditional travel demand models and that can be automatically updated on a regular basis. In pursuit of this goal, this project explored location history (LH) data as an alternative to traditional travel surveys for modeling individual travel patterns. Through LH data, it is possible to view all the places visited (and modes used) by an individual on a specific day. For instance, Google Location History (GLH) is automatically recorded from any device which has its location services turned 'on.' Sadeghvaziri et al. proposed procedures for processing and utilizing GLH data for travel pattern analysis [1]. However, GLH data itself does not provide any information on the socio-demographic attributes and modal preferences of individuals. Addressing this gap, a tool consisting of a mobile app backed by a server and automated data processing system has been developed and deployed. This tool was initially called e-mission when originated by researchers at the University of California, Berkeley [2], but it has since evolved into the NREL-supported capability known as Open Platform for Agile Trip Heuristics (OpenPATH[5]). In addition to collecting location-based travel history data, OpenPATH provides the flexibility to deploy small user surveys to obtain information regarding individual socio-demographic attributes. OpenPATH thus delivers the best of both worlds: i.e., combining traditional travel survey and advanced location-based data collection methods.

Objectives

The key objectives of the project are to:

- Assess the viability of LH data for travel pattern prediction
- Using LH data, compare accuracies of logit and machine learning (ML) models in predicting:
    - what activity to participate in next (i.e., activity type choice)
    - when to start a journey to reach the next activity (i.e., departure time choice)
    - which mode to use to get to that activity (i.e., mode choice).

[5] https://www.nrel.gov/transportation/openpath.html

Approach

The project team had originally planned to collect trip data, coupled with a small (~5 minute) socio-demographic survey using the OpenPATH mobile application. The idea was to solicit responses from a modest sample of (roughly 75–100) researchers from NREL. Although the logistics required for the data collection were in place, the lengthy cybersecurity and data sensitivity approval processes, not to mention complications from the Coronavirus disease (COVID-19) pandemic, disrupted the original plan. The team explored using other "similar" datasets collected through OpenPATH and was able to use a sample dataset collected for an e-bike mini pilot in Colorado. While the dataset was not as large as was originally envisioned for the project, it had depth: 13 participants provided data from November 2020 to January 2021, and this included detailed trip-level information as well as socio-demographic characteristics of the individuals. At the trip level, OpenPATH automatically logs trip start and end times, route taken, as well as the inferred travel mode. Respondents are then prompted by the application to confirm or modify the mode and trip purpose information to ensure accuracy. From a total of 4,163 trips made by the respondents over the data collection timeframe, 2,785 trips had complete information and were used for analysis. The app plus survey data collected through OpenPATH were consolidated in a database. The trip latitude/longitude data were intersected with spatial databases to gather information regarding built environment at both ends of the trip. Socio-demographic, trip, and built environment characteristics were used as features to model activity type, departure time, and mode choices made by individuals. A traditional statistical model (namely the multinomial logit (MNL) model) and a ML model (namely the Random Forest (RF) model) were estimated using similar features so that the performance of the models could be compared and contrasted.

Multinomial Logit Model: The MNL model is a standard statistical model that can best be described as a classification method. The utility function of MNL is defined as:

$$V_i = \alpha + \sum_{j=1}^{J} \beta_j x_j + \varepsilon_i$$

The probability of choosing alternative i is written as:

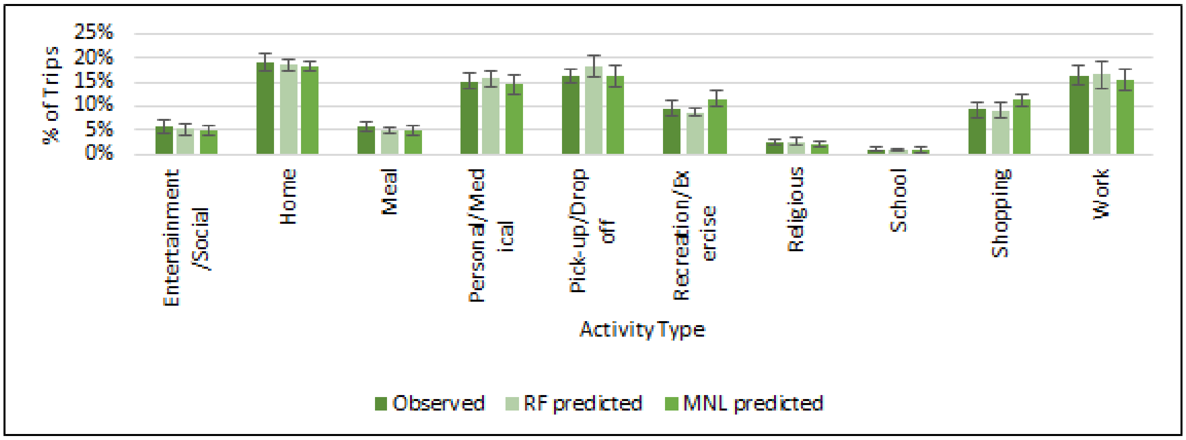
$$P(i|C) = \frac{e^{V_i}}{\sum_{k=1}^{K} e^{V_k}}$$

Where: α is the constant value; J is the total number of alternative attributes considered; β_j is the parameter value of attribute x_j; k represents each alternative in the choice set; K is the total number of alternatives in the choice set; C is the choice set.

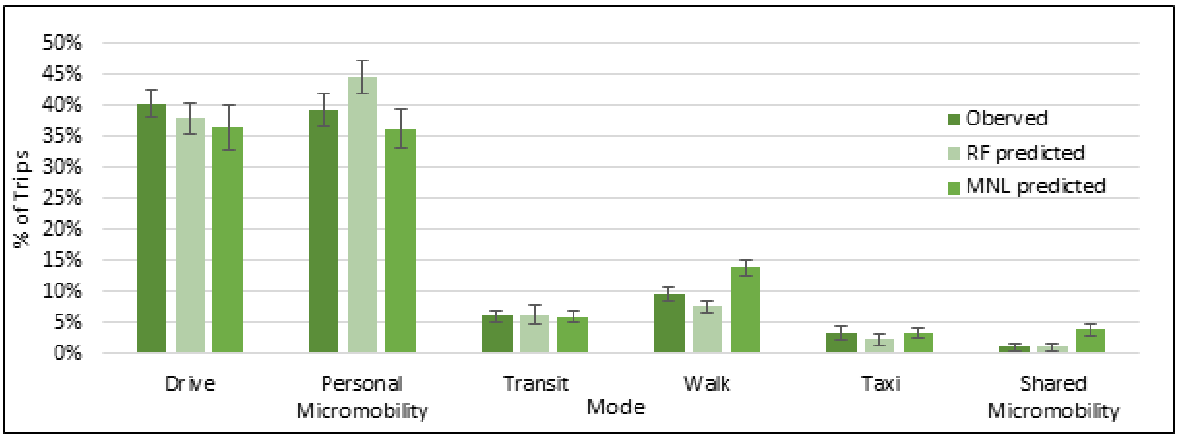
Random Forest Model: RF belongs to the class of decision tree learning methods and can be used for regression as well as classification models. Each tree model is a series of random splits for each feature in the sample data. Estimation occurs by traversing the tree from root (top) to leaf (bottom), where a prediction is stored.

Results

Cross-validation was performed with 10 test/train split sets (a typical approach for evaluating model performance). The results, shown in Figure I.9.1, are based on the average of the ten model runs.



(a) Activity Type Choice Model Results



(b) Mode Choice Model Results

Figure I.9.1 Comparison of (a) activity type choice, and (b) mode choice prediction results. Source: NREL

From the figure, it can be observed that RF and MNL models capture the observed trends in activity type and mode choice reasonably well, with RF performing slightly better than MNL. While the results in Figure I.9.1 show distributional accuracy of both the models, Table I.9.1 presents sample-wise prediction accuracies of MNL and RF models for activity type, destination, and mode choice predictions. The number in each cell of the table signifies the percent of data for which the model predicts the exact choice made by the respondent. A high percent value indicates that the model performs well at predicting individual trip-level outcomes. It can be observed from the table that the RF model consistently outperforms the MNL model in sample-wise prediction accuracies across the three choice dimensions.

Table I.9.1 Comparison of Sample-Wise Prediction Accuracies (and Standard Deviations)

Model Type	MNL Accuracy (StdDev)	RF Accuracy (StdDev)
Activity Type Choice	25.1% (σ = 1.82%)	41.9% (σ = 1.93%)
Departure Time Choice	27.4% (σ = 3.1%)	43.7% (σ = 2.87%)
Mode Choice	47.2% (σ = 1.80%)	67.9% (σ = 1.79%)

Conclusions

The objectives of this project were to: (i) Assess the feasibility of location history data for travel pattern prediction, and (ii) Compare the accuracies of ML and logit models in predicting travel choices. Though the project team could not collect data in the manner originally planned, the project goals were accomplished using a small sample dataset collected for the Colorado e-bike mini pilot program. MNL and RF models were estimated using the processed data, proving that LH data can be used for travel pattern prediction. Model estimation revealed that the ML model consistently performed better than the logit model (particularly at the sample level) in predicting activity type, departure time, and mode choices.

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2. Shankari, K., Mohamed Amine Bouzaghrane, Samuel M. Maurer, Paul Waddell, David E. Culler, and Randy H. Katz. "E-mission: An open-source, smartphone platform for collecting human travel data." *Transportation Research Record* 2672, no. 42 (2018): 1–12.

Acknowledgements

The PI would like to acknowledge the efforts of the NREL team (Rob Fitzgerald, Bingrong Sun, Kalyanaraman Shankari, and Andrew Duvall) in accomplishing the objectives of this project.

The project team offers thanks to Jacob Ward and Raphael Isaac at DOE for their support and encouragement throughout the course of this project.

I.10 Applied Modeling and Simulation Analysis (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $300,000	DOE share: $300,000	Non-DOE share: $0
Project Funding (FY20-FY21): $600,000	DOE share: $600,000	Non-DOE share: $0
Total Expected Project Funding: $900,000	DOE share: $900,000	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], a simulation tool developed by Argonne, to quantify the techno-economic benefits of technologies funded by the DOE VTO. This project integrates VTO-sourced data on component-level technology performance and cost to generate vehicle-level metadata based on U.S. standard driving cycles, with these results useful for informing other analysis activities. In addition, Autonomie vehicle models are used to support additional activities within VTO (e.g., with regard to LCA, economic impact, market penetration, and individual component technologies) as well as 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 target-achieving cases) to represent current and potential future scenarios.

- Develop a database that includes vehicle energy consumption and cost, and detailed component information, including power, energy, cost, efficiency, and operating conditions on the U.S. standard driving cycles.
- Draft a report describing the main assumptions and results, as well as an analysis that to be provided through a detailed excel sheet or a Tableau Server.

Approach

To achieve the objectives outlined above, Argonne identified the following tasks shown in Table I.10.1.

Table I.10.1 Argonne Project Tasks

No.	Tasks	Status
1	Quantify vehicle energy consumption and cost estimation	Complete
2	Analyze the impact of individual technologies on energy and cost	Complete

Task 1 aimed to quantify the energy consumption and cost of various types of vehicles. The scope of this task extended from small passenger cars in light-duty segments to large, long-haul trucks in heavy-duty segments. Several vehicles were identified to cover the large variety of vehicles needed to represent the light-, medium- and heavy-duty segments. This study examined the differences in vehicle requirements and use cases in 10 types of LDVs and more than 20 types of MDHD trucks. The assumptions used for defining these vehicles were based on inputs that were provided by VTO's U.S. DRIVE [2] and 21CTP (21st Century Truck Partnership[SM]) [3]. This work used updated powertrain and sizing assumptions based on these inputs. The main simulation tool used for this work was Autonomie. In addition to Autonomie, a techno-economic analysis tool named BEnefit ANalysis – BEAN – was also used in this project which provides a convenient user interface for the users to examine the sensitivity of the TCO of a vehicle to the component efficiency and cost assumptions.

Efforts supporting Task 2 resulted in a process to identify the value of improving different vehicle technologies in trucks. This task examined several component technologies that are of interest to DOE and industry and quantified the monetary benefits to the consumer if incremental improvements were to be made to these components. Battery, motors, engines, aerodynamics, lower rolling resistance, etc., were all examined as part of this work. The analysis was aimed at helping to identify the technologies that yield the most "return on investment" for both manufacturers and consumers.

Results

Results from FY 2021 analysis activities are included in this section and follow the outline by task, as used in the approach section.

Task 1. Quantifying vehicle energy consumption and cost estimation

The main output of this task is a report that covers the assumptions, vehicle sizing, and simulation results of MDHDVs. The databases accompanying the report give the details of all vehicle-level assumptions, fuel economy observed on regulatory cycles, and the estimated manufacturing cost and operational cost of each vehicle. The FY 2021 report and the databases are accessible from our website [4].

This dataset forms the basis of LCA and other DOE-funded market penetration predictions. The Annual Technology Baseline project by NREL [5] also relies on the vehicle simulation results from this work.

The report presents a quick overview of the results available in the database. Vehicles and technologies for future time frames were modeled in this work. Two potential scenarios for technology progress were examined: the first one a "business-as-usual" scenario (low), and the second one based on a more aggressive level of technology progress (high). For light-duty vehicles, a third scenario is also considered in which all technologies expect both lightweighting advances alongside the "high" level of technology progress. This was done to better understand the effect of energy savings and cost increases associated with lightweighting for each type of vehicle.

The simulation results provide insights into how the vehicle component requirements are likely to change in the years to come as a result of accompanying technology advances. In addition to the component requirements, the database also provides information on projected vehicle-level cost, weight, energy consumption, and cost of driving and ownership for various powertrains. This helps in understanding when advanced powertrains might achieve functional and economic parity with other competing choices. Figure I.10.1 shows the weight, cost, energy consumption, and TCO of hybrid, FCEVs, and EVs as a function of the corresponding values of the conventional diesel truck. This particular analysis projects a gradual reduction of the cost and weight penalties for all powertrains. In fact, this study finds that electric and fuel-cell trucks will be able to compete with diesel trucks even in this segment if the high level of technology progress assumed in this study is met.

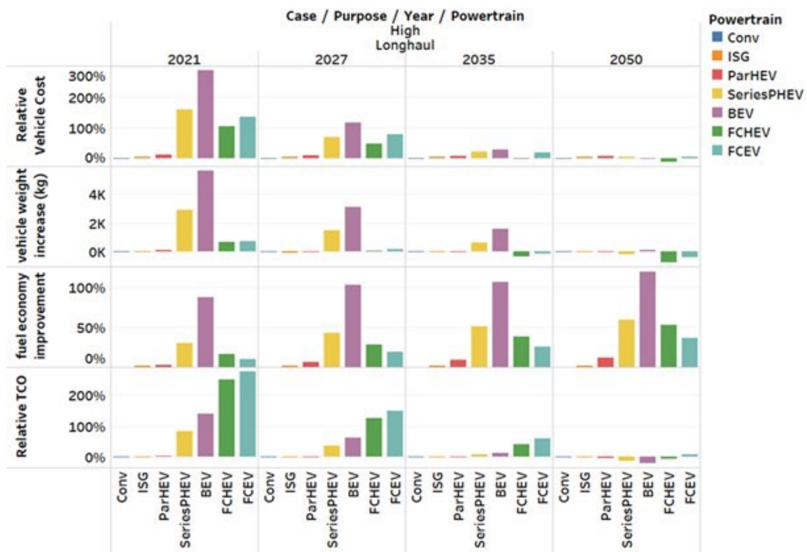

Figure I.10.1 Evolution of vehicle cost, weight, and energy consumption for long-haul trucks that use advanced powertrains. All percentages are computed based on the conventional truck parameters for that year. Source: ANL

Task 2. Value of individual technology improvements

MDHDVs consume approximately 24% of the overall energy from the transportation sector [6]. In this study, we focus on three truck applications, which are defined as part of the DOE-sponsored 21CTP: long-haul trucks, regional-haul trucks, and Class 6 Box trucks [2]. We investigate the improvement of technology with a focus on conventional vehicles and BEVs.

A detailed report was submitted to DOE on this topic, and a paper is also under development. The report will be soon available on the Autonomie website [7]. This annual report provides a quick overview of the scope and results of this task.

The technology improvements assessed in this task relate to the following factors: electric machine and power electronics efficiency, battery energy density, aerodynamics, lightweighting, and tire rolling resistance. We start by quantifying the impact of technology on a 2020 and 2030 long-haul BEV. We then extend the analysis to a 2030 regional-haul truck and a 2030 Class 6 Box truck. Finally, we compare the value of technology improvement for electric and conventional powertrains, with a focus on both the long-haul BEV and the Class 6 Box truck.

In this study, the savings predicted are based on the overall cost of driving the vehicles. This cost refers to a levelized cost of driving, which is computed as shown below.

$$Levelized\ cost\ of\ driving = \frac{\text{vehicle purchase price} - \text{discounted residual value} + \text{discounted energy cost}}{\text{distance}}$$

The vehicle purchase price is the vehicle cost multiplied by 1.2 of the retail price equivalent. The vehicle cost is determined by adding up the cost of all components.

Table I.10.2 Baseline Values for Sensitivity Studies for Line Haul Trucks

	Year 2020	Year 2030
Motor/inverter combined efficiency	0.91	0.94
Battery pack energy density	158 Wh/kg	273 Wh/kg
Cd	0.52	0.42
Glider weight	10,833 kg	9.305 kg
Tire rolling resistance	5.4 kg/ton	4.9 kg/ton
Auxiliary load	3,400 W	2,600 W

Analysis of 2030 BEV long-haul, 2030 BEV regional-haul, and 2030 BEV Class 6 Box trucks

The impact of technology improvement depends on vehicle assumptions and on duty cycles and operational assumptions. In this section, we compare the results among BEV long-haul, BEV regional-haul, and Class 6 Box trucks based on 2030 assumptions. Comparing long- and regional-haul BEVs, the values of technology improvement in terms of percentage reduction in driving cost shown in Figure I.10.2 are similar for all technologies except aerodynamics.

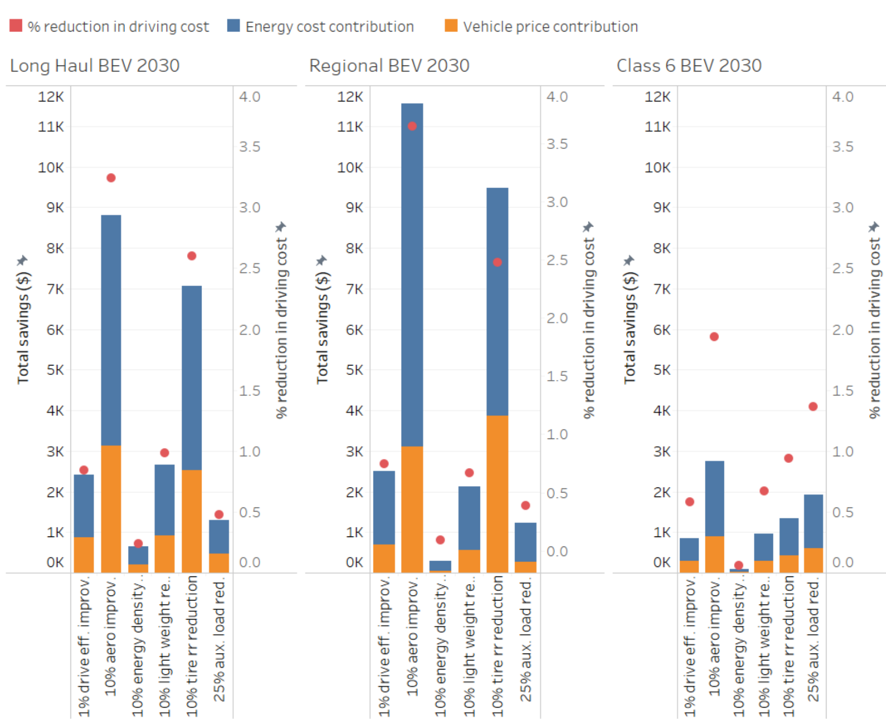

Figure I.10.2 Value of technology improvements for 2030 long-haul and regional-haul trucks and Class 6 Box trucks. Source: ANL

The higher charge depletion assumption for regional-haul BEVs (0.5 versus 0.42 for long-haul BEVs) explains why the benefit of technology improvement is greater for regional-haul BEVs than for long-haul BEVs. Also, the share of the savings coming from energy cost is greater for regional-haul versus long-haul BEVs and is because regional-haul trucks drive more miles overall (15 years at 50,000 miles per year) than long-haul trucks (5 years at 100,000 miles per year). Class 6 Box trucks show lower reduction in cost of driving for all technology except auxiliary load compared to long- and regional-haul trucks. Due to the low average duty-cycle speed, the benefit of aerodynamic improvement is less for Class 6 Box trucks than it is for Class 8 long haul trucks. While the weight reduction decreases the amount of energy required to move the vehicle, it also limits the regenerative braking in a dynamic duty cycle. The lower daily mileage requirement for Class 6 Box trucks also drives a lower battery size; and, hence, an improvement in battery energy density has less of an impact. Finally, the baseline auxiliary loads (2,600 W for long- and regional-haul trucks and 2,500 W for Class 6 Box trucks) are similar for all applications. Since the average power output to operate a Class 6 Box truck is less than the output to operate long- and regional-haul trucks, the auxiliary load represents a higher percentage of the power output; hence, Class 6 Box trucks are more sensitive to reduction in auxiliary load.

Comparison of 2030 BEV and conventional Class 6 Box trucks

Comparison of the benefits in conventional trucks and BEVs shows the differences in the importance of a given technology for different powertrains. The monetary value associated with reducing vehicle losses through the reduction of glider weight, auxiliary loads, aerodynamic drag, or rolling resistance varies both across powertrains and across time.

When comparing the value of technology improvement between BEVs and conventional powertrains shown in Figure I.10.3, there is no clear trend as to which powertrain benefits more from technology improvement. Overall, the contribution from energy cost savings is greater for conventional powertrains since the average cost of a kWh from the engine (which depends on a combination of engine efficiency and diesel cost) is higher than the average cost of a kWh from the battery (which depends on a combination of battery efficiency, charger efficiency, and electricity cost). This difference is less pronounced for long-haul trucks, with their higher engine efficiency (55% peak engine efficiency for long-haul trucks vs. 45% for Class 6 Box trucks).

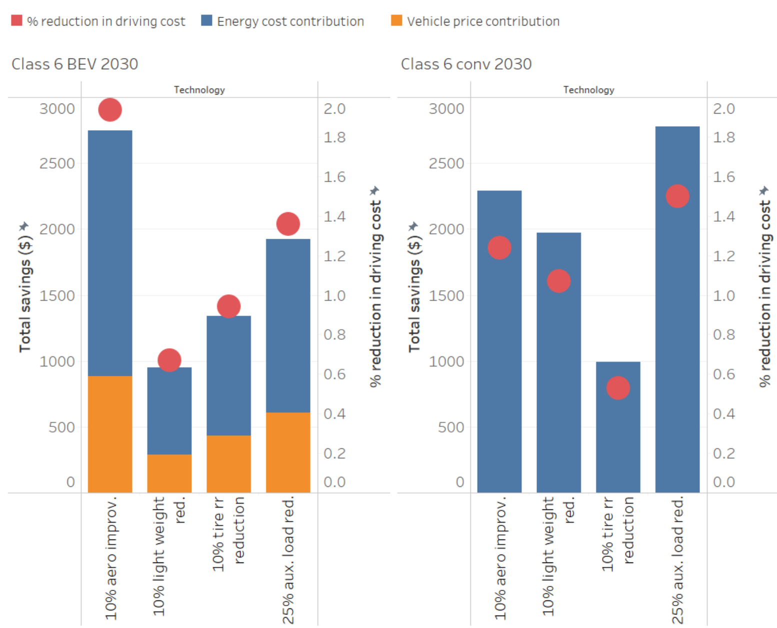

Figure I.10.3 Value of technology improvement for BEV and conventional Class 6 Box trucks. Source: ANL

With BEVs, despite the lower energy cost savings from technology improvement, the overall savings can still be greater due to reduction in battery size.

While Class 6 Box trucks drive at a lower speed, their aerodynamics have not seen the same level of optimization over the years as long- and regional-haul trucks. Other projects have shown that up to 50% reduction in drag coefficient could be achieved, which would result in significant reduction in driving costs. The data points on the far left of each graphic in Figure I.10.3 demonstrate the significant reduction in driving cost that could be achieved with some aerodynamic improvements, a reduction that is particularly pronounced with the BEV.

Improvements in battery energy will primarily benefit applications that require large batteries. The value of technology improvement for BEVs is likely to decrease as batteries become cheaper, whereas technology improvement for conventional vehicles may be more valuable in the future as diesel costs are expected to increase.

To reiterate a key point, with BEVs, technology improvement has a compounding effect in that it benefits from both the technology improvement itself and from the reduction in battery size that the improvement allows. With conventional vehicles, the savings are primarily due to reduction in diesel expenditure.

Conclusions

The team has completed all of the tasks planned for FY 2021. This work has resulted in two detailed reports. The first report covers the energy consumption, performance, and cost of vehicles spanning light-, medium-, and heavy-duty vehicles [4], and the second report focuses on the value of various technological improvements for conventional and electric trucks [7]. The simulation and data analysis support that was provided for U.S. DRIVE technical target development activities has helped various technical teams to determine the appropriate technology development goals needed to achieve comparative cost metric parity with competing vehicles.

Key Publications

Freyermuth, V., Vijayagopal, R., Rousseau, A., “Medium- and heavy-duty value of technology improvement, submitted to Society of Automotive Engineers World Congress 2022 for publication.

Islam, E., Vijayagopal, R., et al. “A Detailed Vehicle Modeling and Simulation Study Quantifying Energy Consumption and Cost Reduction of Advanced Vehicle Technologies Through 2050,” Report to the U.S. Department of Energy, Contract ANL/ESD-21/10, October 2021.

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5. Annual Technology Baseline, National Renewable Energy Laboratory. https://atb.nrel.gov/
6. Transportation Energy Data Book, Edition 39, Oakridge National Laboratory. https://tedb.ornl.gov/wp-content/uploads/2021/02/TEDB_Ed_39.pdf
7. Freyermuth, V., Vijayagopal, R., Rousseau, A., “Medium- and heavy-duty value of technology improvement, submitted to SAE World Congress 2022.

I.11 Electric Vehicle (EV)-Grid Analysis Modeling (Lawrence Berkeley National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $250,000	DOE share: $250,000	Non-DOE share: $0
Project Funding (FY20-FY21): $500,000	DOE share: $500,000	Non-DOE share: $0
Total Expected Project Funding: $750,000	DOE share: $750,000	Non-DOE share: $0

Project Introduction

The transportation sector is undergoing a transformation through the introduction of on-demand mobility and vehicle automation thanks to a variety of emerging mobility technologies [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]. This is especially true in the freight industry, with a particular focus around heavy-duty truck electrification and operations. While there is still a great deal of uncertainty around the exact impact that automated vehicles will have on the transportation system in the coming decades [4],[5] many believe that they could soon become a significant part of the transportation system, dramatically disrupting conventional modes of mobility in the process.

Overall, the urgent need to decarbonize the transportation sector combined with falling battery prices has spurred industry and policy interest in long-haul truck electrification. Understanding the charging behavior and resulting loads from freight electrification will be crucial for smooth operation of the electric grid and will have far reaching impacts on the environment in the form of GHG emissions and air pollution. As such, this project has aimed to assess the benefits of heavy-duty truck electrification and emerging vehicle electrification opportunities in micro-mobility markets using the Grid-Integrated Electric Mobility Model (GEM). This national model simultaneously optimizes the provision and operation of shared heavy-duty autonomous and electric vehicles (SHAEVs) to provide electrified goods mobility alongside an economic dispatch of power generation [6],[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 project has further developed the GEM model to explore the dynamics and impacts of an integrated intelligent transportation–grid system in which mobility is served by either privately owned electrified trucks or SHAEVs, charging is responsive to costs on the grid, and power resources are dispatched in merit order to serve electricity demand.

Objectives

The purpose of this project was to leverage the existing GEM Model and develop new methodological capabilities that enable the simulation of future electrified and autonomous freight transportation systems and micro-mobility and to quantify some of 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 (including estimates of demand rebound and mode shifting for passenger travel), grid infrastructure upgrades necessary to support the growing loads from transportation applications, and the impact on greenhouse gas emissions of the EV-grid systems.

Approach

The project developed an optimization model that solves for the cost-minimizing dispatch of privately-owned and shared heavy-duty vehicles (HDVs) for operation and charging, the allocation of SHAEVs to serve goods delivery, the investment and construction of an SHAEV fleet and supporting charging infrastructure, and the economic dispatch of electric power plants for the U.S. bulk electricity grid. The power sector was included by coupling GEM to the Grid Operation Optimized Dispatch electricity model [8]. This combined model treats the size of the SHAEV fleet and the amount of charging infrastructure as continuous decision variables (relaxing the problem from mixed-integer convex optimization to quadratic programming), allowing for variable 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. Shared autonomous and electric vehicle (SAEV) fleet planning costs are simultaneously minimized by amortizing the cost of the fleet and charging infrastructure to a daily time-period. Furthermore, we also incorporate aspects of micro-mobility into the system by focusing on first-mile/last-mile travel markets electrification, wherein aspects of fleet size, charging range and battery capacities are considered within the optimization framework. We note that a similar algorithm developed for SAEVs in earlier GEM model developments are incorporated into the formulation for both SHAEVs and micro-mobility.

The scope of the GEM model is the contiguous US, and the mobility demands for 13 regions are explicitly modeled. In addition to developing the optimization model, the project team developed a set of empirically derived inputs and assumptions for the model application illustrated in Figure I.11.1. 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 NREL using Electric Vehicle Infrastructure Projection (EVI-Pro) tool.

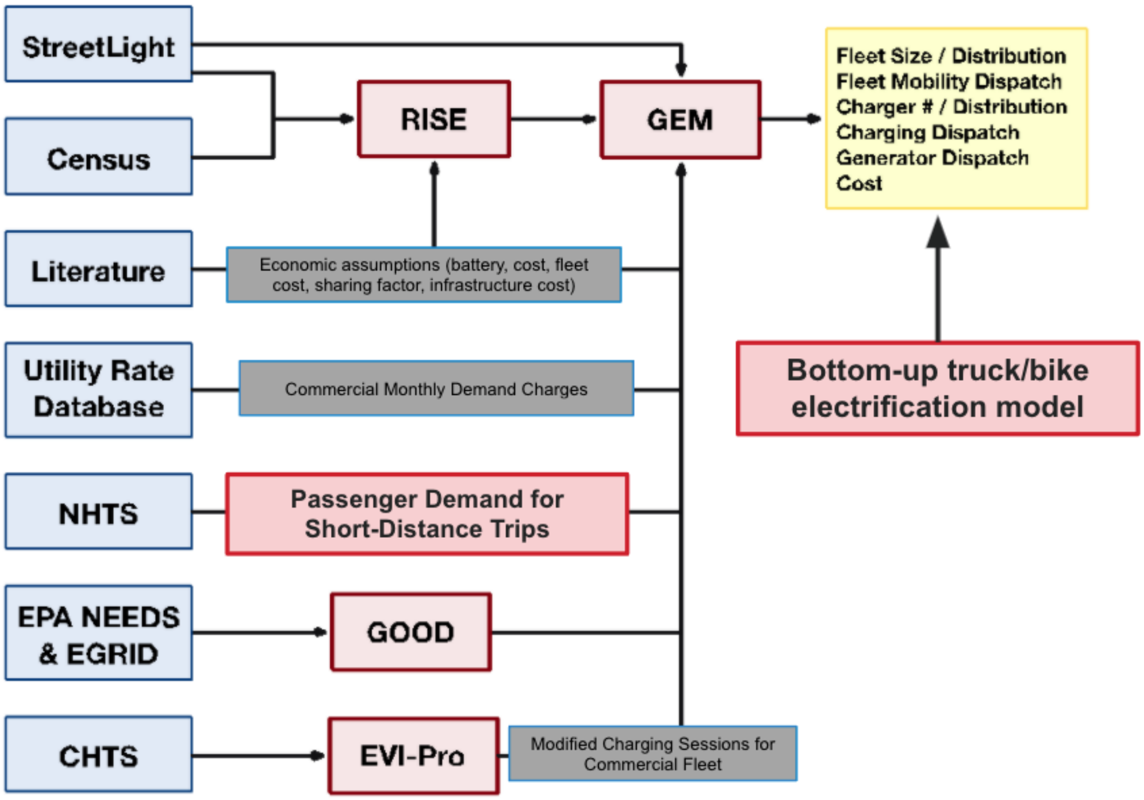


Figure I.11.1 Sources of data (blue), data processing (dark red), models (light red), intermediate data (grey), and model outputs (yellow) in the overall modeling and processing workflow. Source: LBNL

Results

Figure I.11.2 (a) shows the privately owned truck vehicle activity by time of day, wherein the plot clearly demonstrates the larger share of moving vehicles than charging profiles, which contributes to a disproportionate usage of the vehicle fleet based on human-operated ineffectiveness in the system as compared to what would be optimal for supply-demand constraints related to vehicle charging distributions.

Figure I.11.2 (b) shows that automated trucks, on the other hand, optimally manage and increase efficiency in the system, meaning moving away from continuous movement and charging of vehicles to, instead, matching the supply-demand constraints. Overall, the results suggest that SHAEVs are less likely to idle and make fleet operations more efficient than privately owned trucks.

Figure I.11.2 (c) for the SHAEV fleet, decreases by 56% as the fraction of mobility demand met by SAEVs increases from 0% to 100%. 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. The fleet turnover is also faster, due to higher utilization, as S increases.

Figure I.11.2 (d) shows the optimal fleet size of SHAEVs and privately-owned EVs. This figure decreases by almost an order of magnitude from ~200 M vehicles in the S = 0% case (these 200M vehicles are “active” vehicles used on a typical weekday and represent ~56% of the current stock of U.S. HDVs) to ~50M vehicles in the S = 100% case. This occurs because the utilization of the SHAEV fleet is about 12 times higher than that of private trucks due to increased time spent moving, the higher payload (i.e., amount of goods) capacity per trip, and faster recharging times.

Figure I.11.2 (e), also decreases substantially as the fraction of mobility demand met by SHAEVs increases: Peak demand is 161 GW at S = 0% and is almost halved (~89 GW) when S = 100%. The dramatic increase in the SHAEVs' contribution to peak power between S = 50% and 75% can be understood as follows: when S = 50%, the SHAEV loads can still "valley fill" within the private EV load, whereas when S = 75% the SHAEV 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 the expanded charging scheduling available to a full SHAEV fleet. The increase in demand charge cost is outweighed by the reduced vehicle purchase cost of private vehicles.

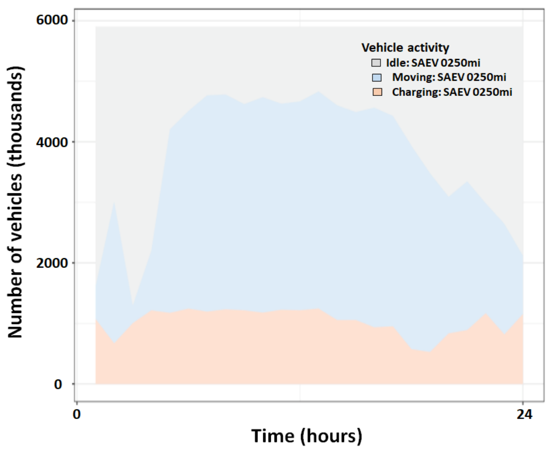
Figure I.11.3 shows results for key outputs from electrification of micro-mobility (i.e., e-bikes) scenarios in the GEM model averaged over time (i.e., the selection of days that we simulated) and geography, displayed across the full range of the fraction of passenger demand satisfied by bike-to-car trip shares.

These scenario results demonstrate that as the share of bike trips increase from 0% to 100% the cost of total ownership (i.e., fleet and infrastructure cost) increases significantly, particularly due to the increase in the number of bike chargers (refer to Figure I.11.3 (a) and (b)). However, the results also demonstrated decreases in overall peak power demand and GHG emissions with 100% replacement of LDVs by e-bikes for short-distance trips.

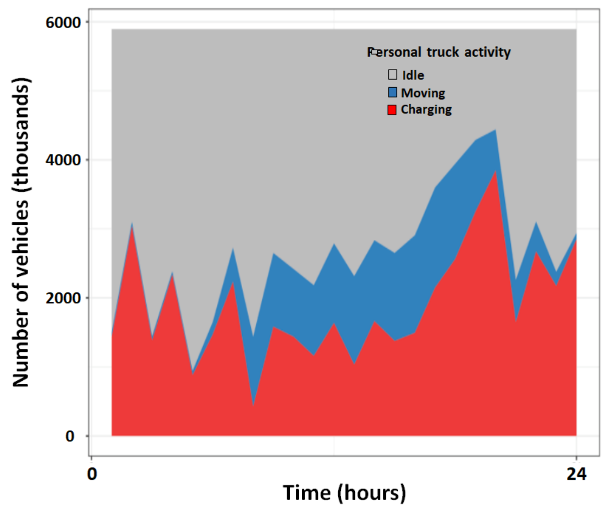
Conclusions

The configuration of the freight system in which SHAEVs serve goods delivery has substantial benefits over one that relies on privately-owned electrified trucks or gasoline-powered vehicles. Overall, the project results suggest that freight automation increases operating efficiency by reducing total costs, leading to faster goods delivery within the transportation system. Lowered GHG emissions, an additional benefit, would also result. 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, SHAEVs 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 leading to more optimal utilization of solar and wind resources (thanks to the flexibility in charging times). Finally, the overall GHG emissions from the mobility system are shown to decrease substantially with a large penetration of SHAEVs, even though GHG emissions are not explicitly modeled in the GEM optimization model.

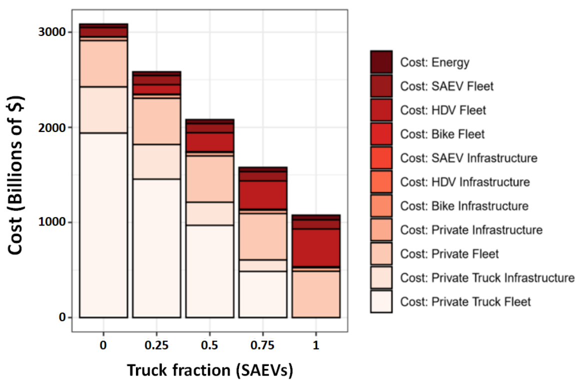
Similarly, project results suggest that electrification of micro-mobility would decrease the overall peak power demand and GHG emissions, though these benefits would accrue alongside an increase in total ownership costs.



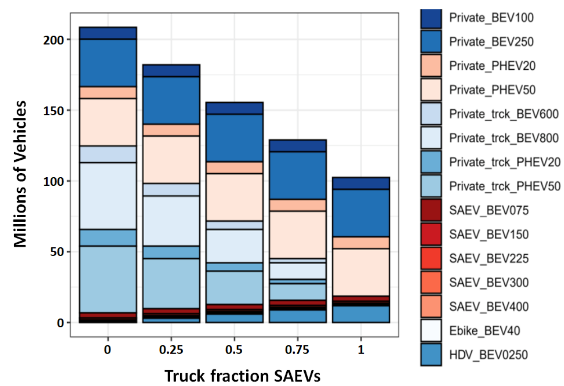
(a)



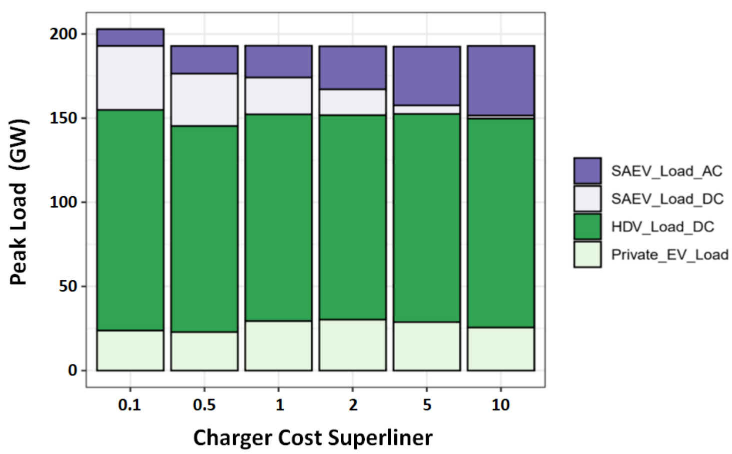
(b)



(c)



(d)



(e)

Figure I.11.2 Truck Electrification Panel: (a) private trucks activity, (b) automated trucks activity, (c) infrastructure cost, (d) fleet size, and (e) peak power demand vs. fraction of SAEV trips (S). Source: LBNL

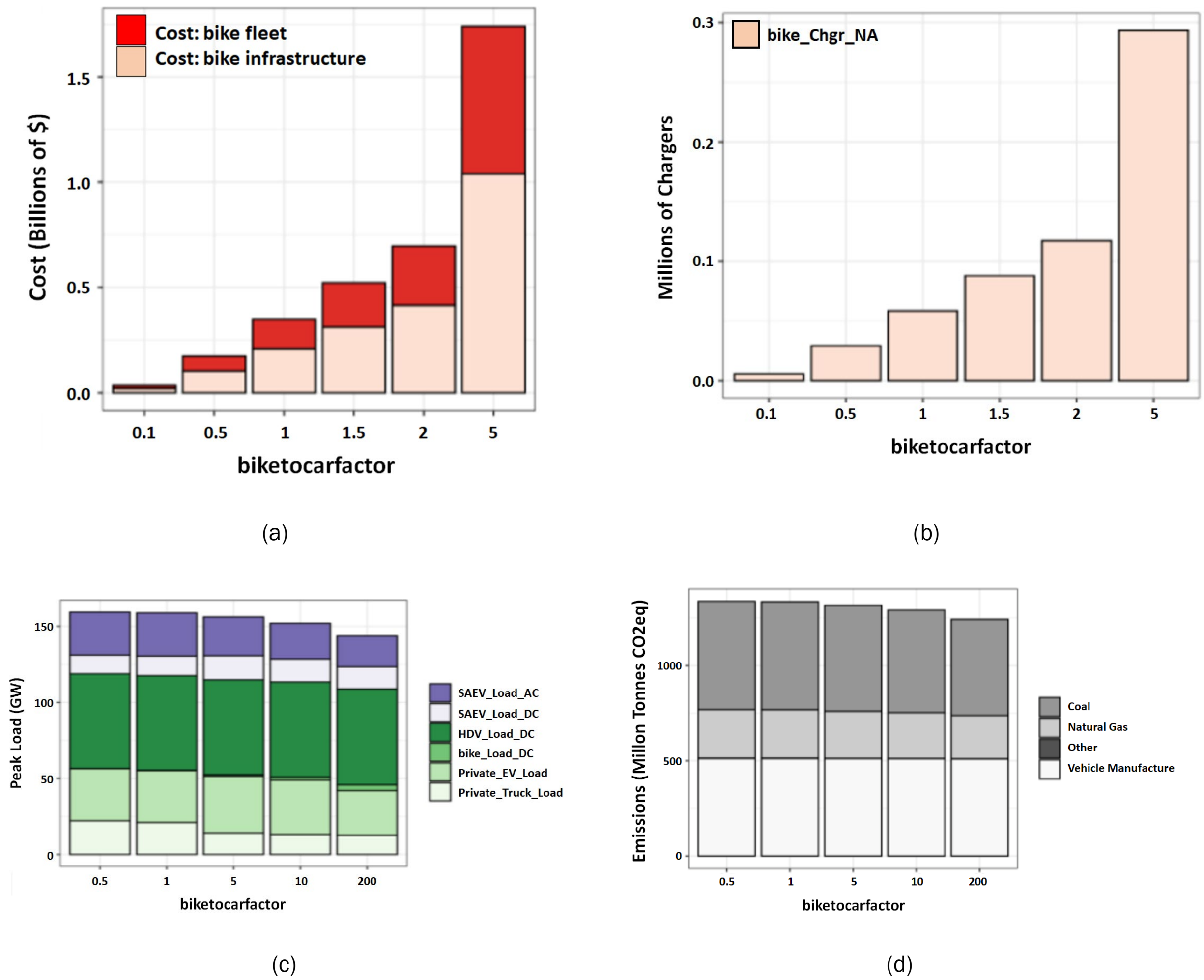


Figure I.11.3 Electrification of Micro-mobility Panel: (a) total ownership cost, (b) number of chargers, (c) peak power demand, and (d) consequential GHG emissions vs. fraction of bike to car trips (S). Source: LBNL

Key Publications

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.

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Acknowledgments

The authors of this work are Srinath Ravulaparthy, Wanshi Hong, Fan Tong, Alan Jenn, and Cong Zhang. We specifically thank Bing Wang from Berkeley Lab for sharing outputs on charging profiles from HEVI-LOAD. The work described was sponsored by the DOE VTO under the VTO Analysis Program. The following DOE EERE managers played essential roles in establishing the project concept, advancing implementation, and providing ongoing guidance: Rachael Nealer, Jake Ward, Raphael Isaac, Madhur Boloor, Kelly Fleming, and Heather Croteau. The authors also acknowledge Tom Stephens of Argonne National Laboratory, a collaborator and contributor to the inception of this analytical work.

I.12 Tracking the Evolution of Electric Vehicles and New Mobility Technology (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $360,000	DOE share: $360,000	Non-DOE share: $0
Project Funding (FY20–FY21): $720,000	DOE share: $720,000	Non-DOE share:
Total Expected Project Funding: $1,080,000	DOE share: $1,080,000	Non-DOE share:

Project Introduction

The DOE VTO invests in quality data and information, both current and historical, regarding all levels of transportation technologies to inform analysis, analysis-supported activities, and relevant stakeholders. VTO has supported the analysis of light-duty market trends in order to assess the potential benefits of VTO-supported technologies and to evaluate program activities. Major challenges include the lack of readily available historical data in the U.S. and other markets, along with a limited geospatial understanding of advanced vehicle sales trends, mobility trends and consumer choice within the U.S. A systematic examination of regional electric drive (E-drive) vehicle purchase trends and mobility usage patterns enable high-quality support and guidance for national impacts analyses (e.g., potential energy and emission reduction) and infrastructure deployment. At the same time, understanding the aggregate impact of electric vehicles is important when exploring electricity use and petroleum consumption. Electric utilities are working to understand the resulting changes in electricity generation, demand, and required infrastructure. Meanwhile, the growth of electric vehicles can offset petroleum consumption by conventional internal combustion engine vehicles, impacting oil prices and extraction described by the Organization of the Petroleum Exporting Countries in 2018 along the way.

Advanced vehicle technologies covered in this study include electric drive vehicles, shared mobility (e.g., transportation network companies, bikeshare, scooter share, etc.), and connected and automated vehicles. Electric-drive vehicle technologies include HEV, PHEV, and BEV.

Objectives

The main objective of this project is to synthesize and improve upon the available data on electrification and mobility technologies in order to evaluate the impacts of these new technologies. The project includes the following tasks:

- Electric-drive vehicle sales and announcement tracking
- New mobility technologies tracking
- PEV national and regional impact assessment
- E-drive vehicle and battery supply chain tracking
- High fidelity PEV technologies characterization

- Sensors for highly automated vehicles (FY 2020 and FY 2021 only).

This project provides quality data and information on electrification and new mobility technologies to the VTO Analysis Program and external researchers. Deliverables include monthly and annual public facing reports, with selected data published on the Argonne website.

Approach

There are six tasks under this project. The following sub-sections describe the method for each task separately.

E-drive vehicle sales and announcement tracking: This task involves collecting E-drive vehicle sales data by make and model from various resources and at different points in time. The research team summarizes the observed market trends and technology evolution of E-drive vehicles in a monthly report that is then distributed to 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 [1].

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 U.S. market, but worldwide announcements are included as appropriate and put into the proper context. This task tracks announcements about electric vehicles, connected and autonomous vehicles technologies, and deployment of new mobility technologies.

PEV national and regional impact assessment: In this task the research team 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 number of batteries available for recycling in the United States and the quantities of specific materials (e.g., cobalt) used. This task will also inform evaluations of regional similarities and differences within the homogeneous PEV market, specifically regionally variable PEV energy consumption profiles (to be completed in FY 2022). Historical nationwide sales data can be linked with state-by-state registration data and knowledge about OEM sales decisions (e.g., the “compliance car” approach in which some car models appear designed mostly to meet a local regulation and are subsequently distributed in limited markets) in order to assess the regional impacts of electric vehicles, including electricity consumption, emissions, consumer costs, and other metrics.

E-drive vehicle Li-ion battery supply chain tracking: Using the PEV sales data collected as part of Task 1, this task involves summarizing the historical battery cell and pack production by manufacturer and production location of the PEVs sold in the U.S. An additional task activity is the tracking of other usage of lithium-ion batteries in HEV and other applications, based on data availability.

New mobility technologies tracking: This task involves collecting market and usage data on new mobility technologies in order to establish an ongoing database of such data and to uncover insights and trends from these technologies that present energy challenges and opportunities. Data is compiled and shared on a variety of new mobility technologies, including but not limited to e-bikes, e-scooters, Transportation Network Companies (TNC), and connected and autonomous vehicles . 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 (e.g., TNC data for the Chicago metropolitan area), depending on source availability.

Sensors for highly automated vehicles: In this task, the research team provides a comprehensive overview of current and emerging automated vehicle hardware, creating the foundation for a range of further technology development and energy impact assessment research. Beyond the in-depth assessment of current automated vehicle hardware, previously alluded to, this task examines the agencies/companies engaged in the space to better understand current and upcoming sensor and processing system capabilities.

High fidelity PEV technologies characterization: Leveraging both published U.S. Environmental Protection Agency (EPA) certification data and data collected via Argonne's dynamometer facility, this task involves providing detailed efficiency metrics based on EPA Corporate Average Fuel Economy 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. FY 2021 work focused on finding the best EPA data source and calculating the efficiency of each plug-in vehicle model from 2011 to 2021. Vehicle models that underwent several generational changes will be highlighted by tracking the year-by-year changes in efficiency aspects and examining which refinements likely brought about those changes.

Results

Over 306,000 plug-in electric vehicles were sold in the United States in 2020, a 4% decrease from 2019. Sales of all-electric BEVs grew 4% to 239,000, while PHEV sales decreased by 25% to 67,000. Relative to the total light-duty vehicle (LDV) market, total PEV shares grew from 1.9% in 2019 to 2.1% in 2020, as overall LDV sales dropped by nearly 15% in 2020. Through 2020, a total of more than 1,700,000 PEVs have been sold, 61% of which have been BEVs. In 2020, the continued decline in PHEV sales coupled with growth in BEV sales, particularly the Tesla Model 3, led to BEVs comprising 78% of the PEV market. Total gasoline displacement by year is graphed in Figure I.12.1. In 2020, 500 million gallons of gasoline were offset by PEVs, with 72% 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 2020, PEVs have offset over 1.9 billion gallons of gasoline, 1.26 billion gallons by BEVs and 640 million gallons by PHEVs. A report released in FY 2021 by the research team [2] documents the details of the methodology used to estimate vehicle miles traveled, weighted efficiency, and the resulting gasoline displacement.

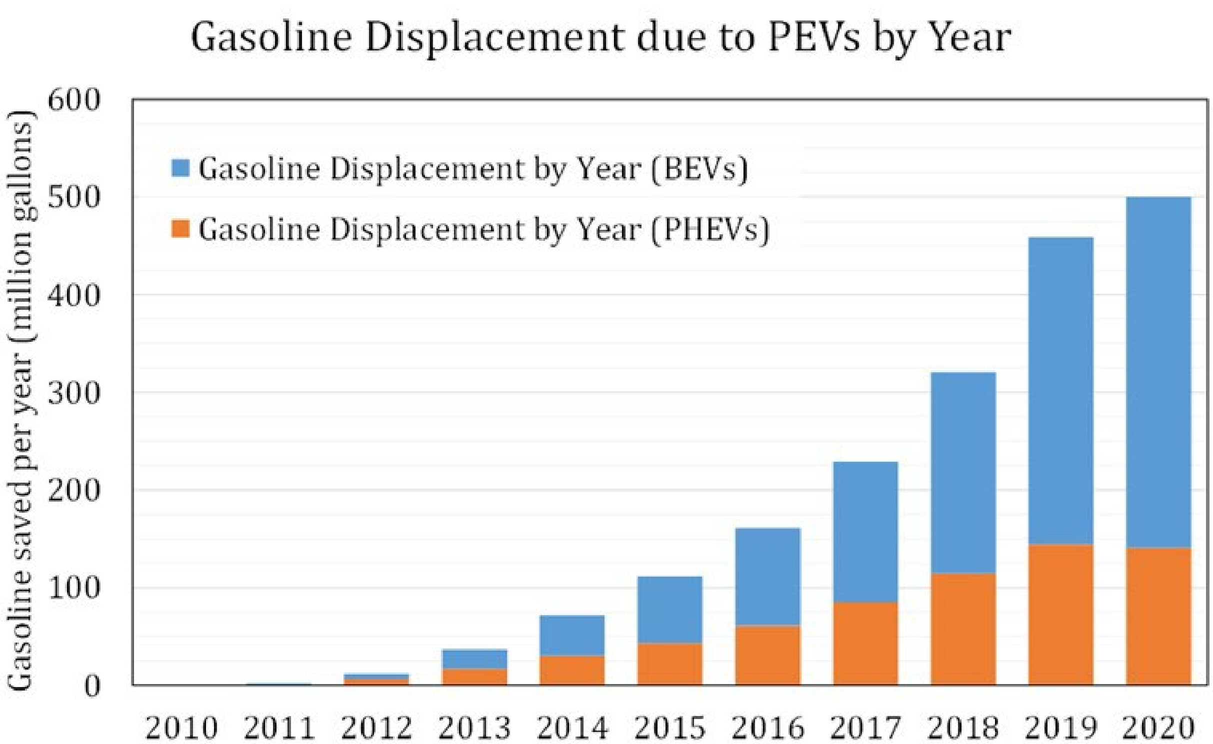

Figure I.12.1 Gasoline displacement by LDV PEVs by year. Source: ANL

The majority of PEVs sold in the U.S. have been assembled in the U.S. and use battery packs built in the U.S. The majority of the component battery cells have come from the U.S., Japan, and South Korea. Other manufacturing locations include Germany and Belgium (vehicles and packs), Poland and Hungary (cells), and Mexico and Canada (vehicles). Figure I.12.2 uses a Sankey diagram to show the supply chain in terms of the production locations of battery cells, battery packs, and vehicle assembly for PEVs sold in the US. The Sankey diagram format makes it easy to track the flow of production from one location to another (i.e., from left to right in the graphic) over several steps of the supply chain. The figure indicates total Li-ion battery capacity (in MWh) supplied to the market by each production location between 2010 and 2020. During this time, a total of approximately 75.9 GWh (75,900 MWh) of battery capacity was installed in PEVs sold in the U.S. Of that total, 65.8 GWh was installed in PEVs that were assembled in the U.S. Of the total battery capacity installed over this period for the U.S. market, 67.4 GWh of battery packs and 39.1 GWh of battery cells were assembled in the U.S.

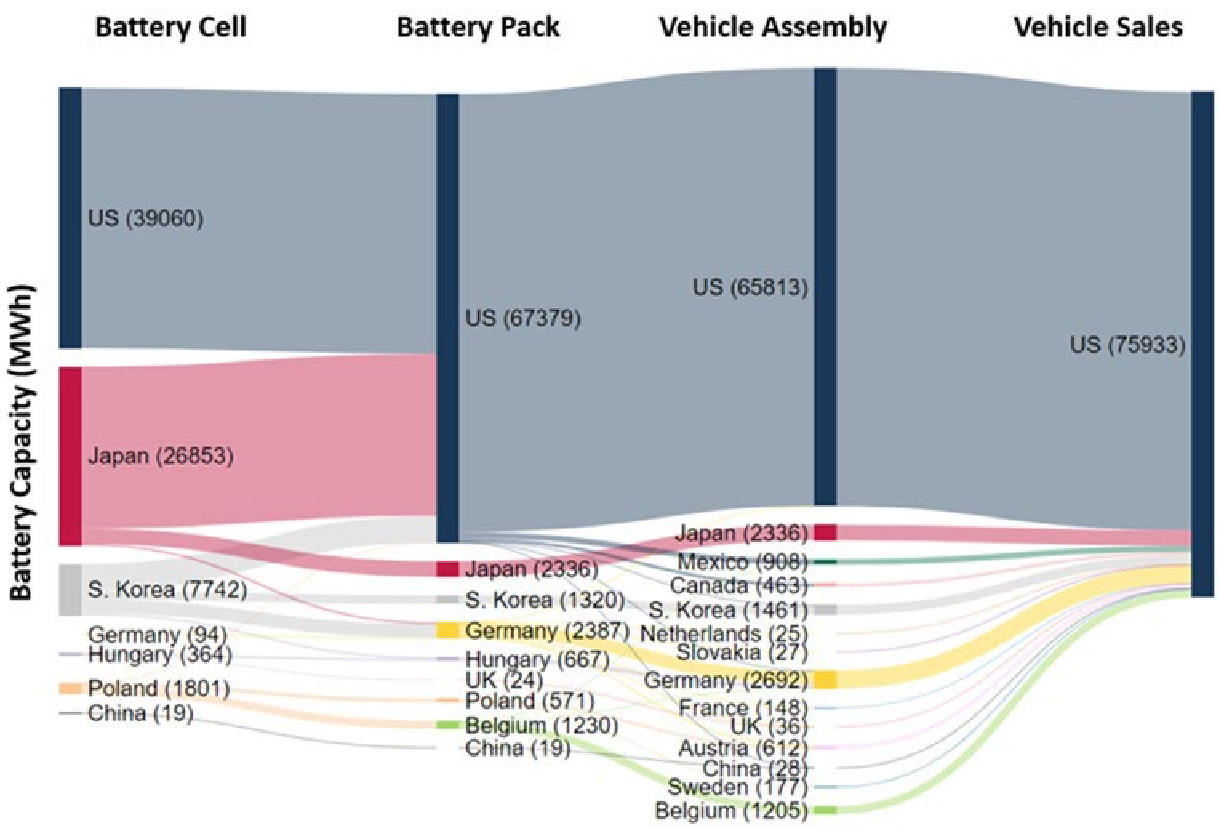

Figure I.12.2 Total capacity (MWh) of Li-ion batteries supplied to the U.S. PEV market by production location, 2010–2020. Source: ANL

The analysis for the third task listed above evaluates shared mobility technology usage in the context of household income and average number of household vehicles by census tract. Figure I.12.3 shows census tracts that are above the 90th percentile in trips per capita by scooters, bikes, TNCs, or some combination of the three modes, alongside a second graphic that displays median income ranges by census tract. Note that the scooter pilot area, the only part of the city for which we have scooter usage data, does not span the entire city. The scooter pilot area is shown in both maps by the dotted black lines. Census tracts with high mobility usage are generally correlated across all three mobility types and are highly correlated with high income. While not shown in this figure, the analysis also found that census tracts with higher household income and fewer household vehicles tend to have higher TNC usage per capita, and similar trends are seen with bikeshare and scooter share usage.

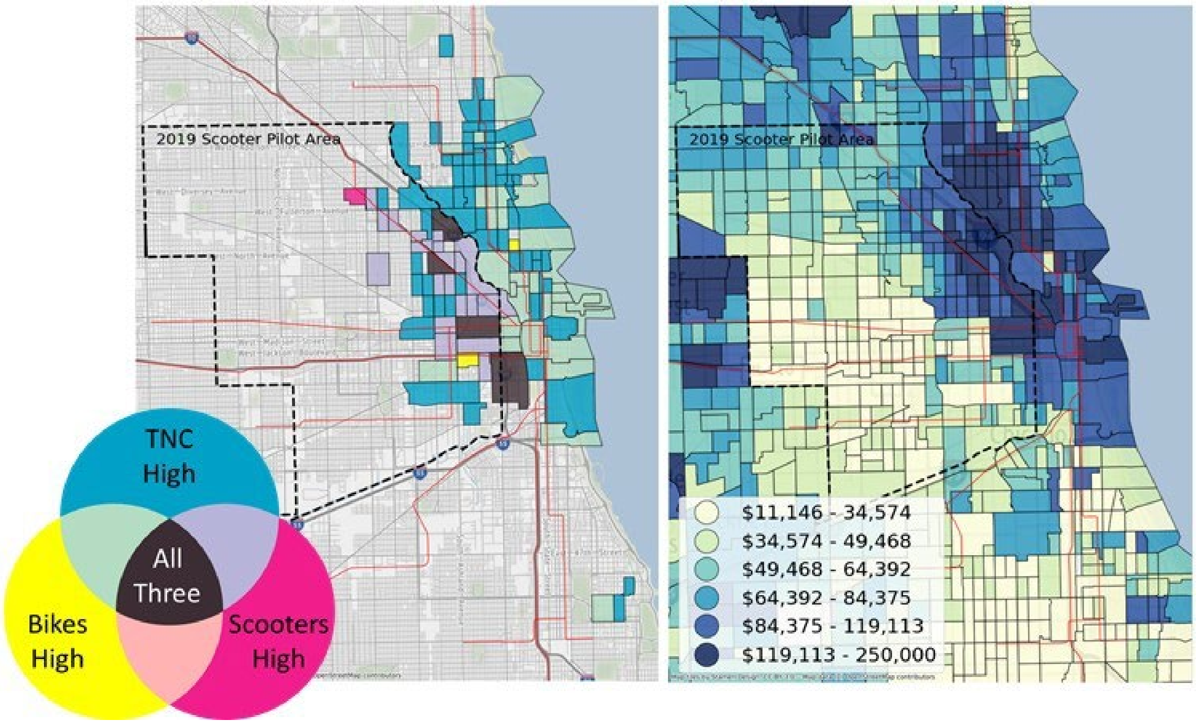

Figure I.12.3 Census tracts with over 90th percentile in trips per capita by scooters and bikes, TNCs or combination of the three (left); Median Income ranges by census tract (right). Source: ANL

Addressing the fourth task listed above, highly automated vehicles are a new mobility technology that holds great promise but also great uncertainty. One area of uncertainty is the capability of required hardware that is needed to drive safely, including computational needs and sensors. Cameras are low-cost and high-resolution optical sensors that capture images of light. Lidar utilizes laser light to measure distances through a process called ranging and is seen as a high-quality and high-range sensing option, though one with a relatively steep cost. Radar uses radio waves to measure range, angle, and velocity of surrounding objects. Ultrasonic sensors utilize high frequency sound waves to map out their short-range surrounding environment and are excellent for proximity detection regardless of environmental conditions. As shown in Figure I.12.4, sensors have grown exponentially in performance and efficiency, though power draw has also increased over time.

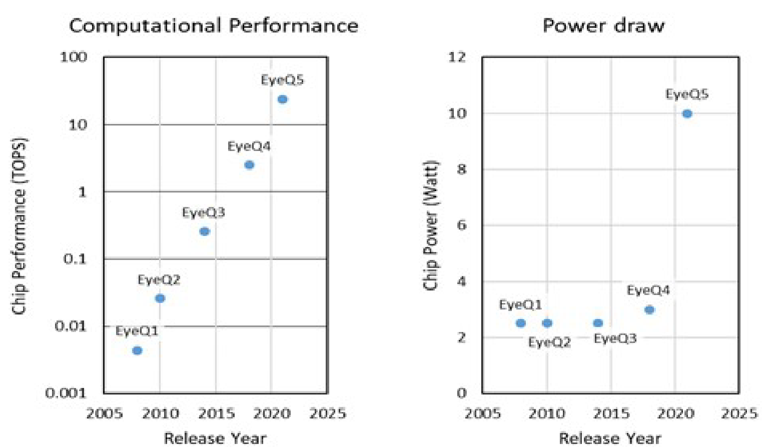

Figure I.12.4 Representative performance for a visual recognition microchip designed for autonomous vehicles. Source: ANL

Addressing the final task above, in FY 2021, several new BEV models entered the market. The new EPA certification results were gathered and entered into the powertrain efficiency calculation code, resulting in an updated database of vehicle efficiency metrics for all BEVs in EPA's certification database. Tracking the trends can lead to insights into the state of current technology and possibly predict trends into the future. As noted in the previous year's update, vehicle range is rapidly increasing, and this makes for expected increases in energy consumption resulting from added weight of the larger batteries required. However, this analysis separates increases in vehicle energy requirements from added weight from efficiency achievements in the powertrain by looking at powertrain efficiency calculations (defined as positive cycle energy at wheel / alternating current (AC) energy consumption over a given cycle). There were significant jumps in powertrain efficiency between 1st generation and later generation models from the same OEMs (around model year (MY) 2016 and 2017) and, in aggregate, this has created an upward trend in powertrain efficiency over a timespan starting from MY 2011 to around MY 2018 or MY 2020.

Somewhat concerning, with the updated data, not only can we see vehicle economy (energy consumption / distance) worsening in model aggregate (i.e., due to added range and larger vehicles), but the powertrain efficiencies appear to have begun a downward trend for both the urban and highway tests. The updated "powertrain efficiency" results are seen in Figure I.12.5 below. In the urban test, the MY 2022 models have dropped compared to earlier years. In the highway test, the trend appears to have started in 2020. These trends suggest that, with range, weight, and power all increasing, without substantial increases in powertrain efficiency, the trend towards increased energy consumption across the overall PEV fleet is likely to continue and perhaps even accelerate.

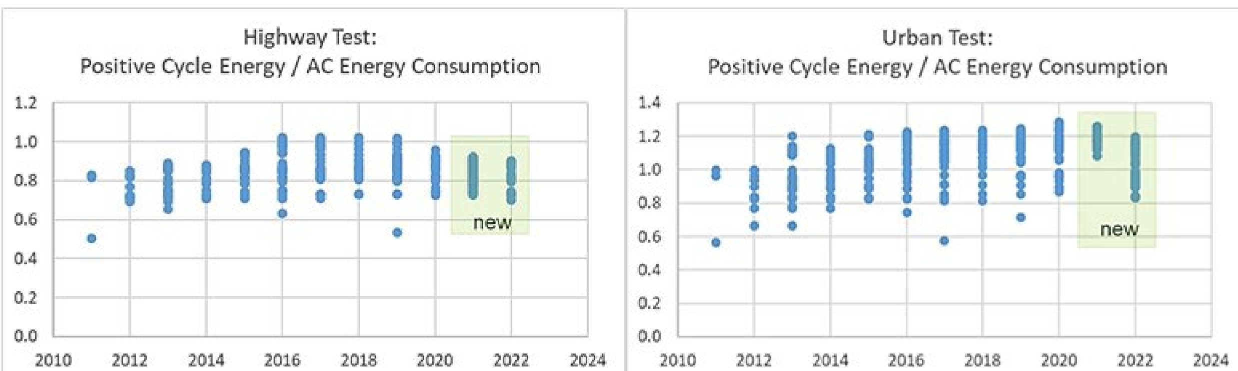

Figure I.12.5 "Powertrain Efficiency" results showing drop in aggregate model efficiency. Source: ANL

Tesla is doing a good job of mitigating added battery weight with high powertrain efficiency. The company is also mass-producing a smaller Model 3 and Model Y (the latter with a very high calculated chassis economy—i.e., the mechanical energy per unit distance required to drive the vehicle). Other OEMs are now entering the market with larger, SUV-sized vehicles. This should be expected as battery costs go down, battery pack size increases, and vehicle sizes also increase—this latter factor lowering chassis economy and thus worsening overall energy consumption.

Conclusions

PEV sales remain approximately 2% of the U.S. LDV market in 2020. Over 1.7 million PEVs have been sold, driving 52 billion miles on electricity since 2010, thereby reducing national gasoline consumption by 0.42% in 2020 and by 1.9 billion gallons, cumulatively, through 2020. Most BEVs sold in the United States are manufactured in the U.S., while most PHEVs are imported. The batteries used in PEVs sold in the U.S. have been largely domestically sourced. In terms of total battery capacity since 2010, over half of all cells have been produced in the U.S., as have nearly 90% of all battery packs.

New mobility options are growing in cities nationwide, but their use is not distributed evenly across all demographic segments. High mobility usage is centered in high income areas despite these areas also having good public transit accessibility.

With increasing electric range, vehicle size, vehicle weight and power, the overall vehicle economy (energy consumption / distance) is worsening and powertrain efficiencies decreasing. The most efficient PEVs are four-wheel drive models because this is achieved by adding another motor. This is a pattern that stands in contrast to what is seen within the conventional car fleet, which achieves four-wheel drive by adding more gears.

Key Publications

Gohlke, David, and Zhou, Yan. Assessment of Light-Duty Plug-in Electric Vehicles in the United States, 2010 – 2020. United States: N. p., 2021. Web. doi:10.2172/1785708.

Zhou, Yan, Gohlke, David, Rush, Luke, Kelly, Jarod, and Dai, Qiang. Lithium-Ion Battery Supply Chain for E-Drive Vehicles in the United States: 2010–2020. United States: N. p., 2021. Web. doi:10.2172/1778934.

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Acknowledgements

The authors thank David Howell, Jacob Ward, Steven Boyd, and Raphael Isaac of the VTO for their continued support of this project and constructive comments. The authors also thank Stacy Davis and Robert Boundy of ORNL for providing sales data.

I.13 Assessing Vehicle Technologies Office Benefits in a Transportation Energy Ecosystem (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (Initial): $300,000	DOE share: $300,000	Non-DOE share: $0
Project Funding (FY20-FY21): $600,000	DOE share: $600,000	Non-DOE share: $0
Total Expected Project Funding: $900,000	DOE share: $900,000	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 all the variety of vehicle usage found in the real world. In this project, we use a transportation system model to generate all drive cycles within a geographical area. Advanced vehicle technologies as defined by the DOE VTO are then used to define energy consumption for different timeframes and under different scenarios.

Objectives

During the first year of performance in FY 2020, the project focused on light-duty passenger vehicles and defined powertrain distributions that provide the lowest cost of driving. This year, one objective was to extend the analysis to commercial vehicles. The analysis differentiates between medium- and heavy-duty vehicles as their corresponding duty cycles show distinct characteristics that impact the value of electrified powertrains in each sub-sector. A second objective was to study the relationship between the penetration of plug-in electric vehicles and the number of available public charging stations. This second objective focuses on light-duty passenger vehicles and is a collaboration between Argonne and NREL.

Results

Estimated cost of driving for different powertrains across medium- and heavy-duty applications

POLARIS [1], a mesoscopic transportation system model, provides trip information by defining average speed on network links. The speed information is then fed into SVTRIP [2], which uses a stochastic approach to develop 1 Hz dynamic vehicle speed profiles for each MDHDV within the Chicago metropolitan area. The Autonomie [3] tool, a detailed vehicle level model, is then used to determine the energy consumption and cost of each vehicle across five distinct powertrains:

- Conventional
- Integrated Starter Generator
- HEV
- PHEV

- BEV.

Each vehicle is assigned a Vehicle Miles Traveled (VMT) annual value based on a VMT distribution as defined in the TEDB [4]. Annual VMT is used to determine the amount of energy consumed on an annual basis for each vehicle. In future studies, when route algorithms are fully implemented in POLARIS, VMT will be inferred directly from the POLARIS routes. The POLARIS trip dataset used in this study is as follows:

- Medium-duty (MD)
    - 5072 trips
    - Average trip distance = 6.2 miles
    - Average trip speed = 35 mph
- Heavy-duty (HD)
    - 5012 trips
    - Average trip distance = 37 miles
    - Average trip speed = 46 mph.

MD BEV are sized for 150 miles all-electric range while HD BEV are sized for 500 miles all-electric range. MD PHEV are sized for 75 miles all-electric range while HD PHEV are sized for 250 miles all-electric range. Cost of driving is determined for each vehicle as follows:

Cost of driving ($/mile) = manufacturer's suggested retail price (MSRP) – residual value + energy cost)/distance

Where:

- MSRP = Manufacturing cost * 1.2 (Retail Price Equivalent)
- Residual value assumes 15% depreciation over the service time
- Energy cost = discounted cost of energy over the service time
- Distance = VMT multiplied by service time
- Ownership period is set to five years for HD and 15 years for MD
- Discount rate of 4%.

For each vehicle, the powertrain that provides the lowest cost of driving is selected. Figure I.13.1 highlights the share of powertrains that provide the lowest cost of driving. Results are split between HD (Class 7 and 8 tractor trailer combinations) and MD (Class 3 through 6 single unit). The analysis assumes three different timeframes: current term (CT), short term (ST), mid-term (MT), and long term (LT) and two levels of technology achievement: low and high. "Low" assumes minimal progress in technology advancements and "high" represents a situation where the VTO targets are met. The level of electrification increases in future scenarios due to reduction in technology cost over time, in particular the reduction in battery cost. Results also indicate that the level of electrification is significantly higher in MD compared to HD. For HD, conventional, integrated starter generator, and hybrids still represent a significant share of powertrains even in future scenarios, the only exception being the long-term high scenario. This indicates that further technology improvement would be required in the heavy-duty segment to increase the share of plug-in electric vehicles. Figure I.13.2 shows the corresponding VMT share and highlights that the VMT share of PHEV and BEV is significantly higher than the corresponding powertrain share. In other words, PHEV and BEV tend to drive more than vehicles with lower levels of electrification. PHEV and BEV are preferred when VMT is high because the energy cost is lower, and they need the longer VMT to compensate for the higher purchase price.

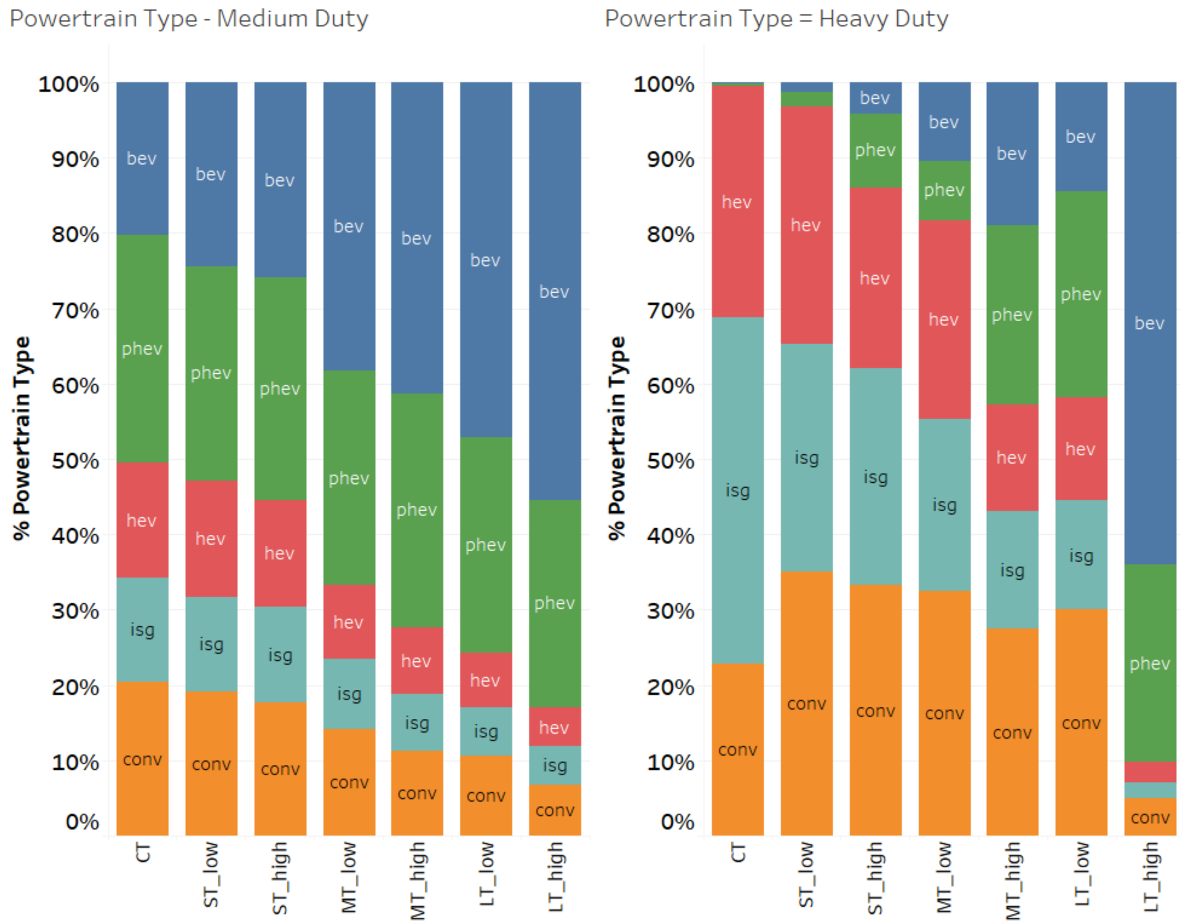

Figure I.13.1 Powertrain share for each timeframe and technology level. Source: ANL

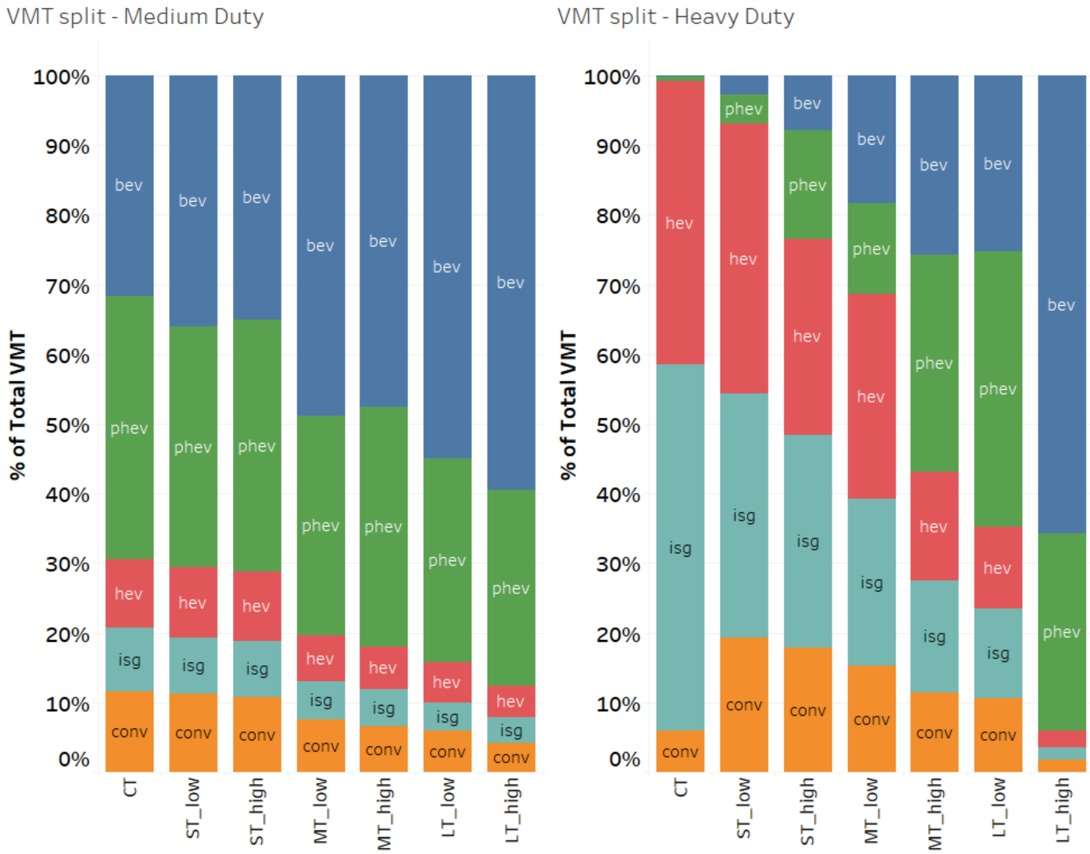

Figure I.13.2 VMT share per powertrain type across timeframe and vehicle technology. Source: ANL

Interaction between the number of public charging stations and the number of plug-in electric vehicles

POLARIS models the interaction of traveler behavior (i.e., activity generation, activity scheduling, destination choice, mode choice, route choice, etc.) and supply-side response (traffic congestion, transit vehicle loads). Energy consumption estimation is usually done in a post-process step where outputs from POLARIS are fed into SVTRIP and Autonomie. However, if a BEV battery gets low and needs to be charged, this would affect the activities of the driver as he may decide to go to a charging station or cancel activities that he had scheduled and that in turn would affect traffic conditions. For POLARIS to model those effects, it needs to keep track of battery state of charge (SOC) in real time as the simulation runs. The charging behavior of a traveler and the electricity consumption of BEVs are then integrated in POLARIS. The decision to charge is affected by the current SOC, distance to the nearest charging station, home charger availability, and potential scheduling conflicts. A ML model is used to estimate the link-by-link energy consumption of an EV based on vehicle and network characteristics.

Overall system performance is dependent on the market penetration of EVs, home charger availability, the location of charging stations, plug types, and the number of plugs. In this project, we have focused on two cases:

- High EV ownership, low home charging availability
- High EV ownership, high home charging availability.

Vehicle ownership assumptions come from the SMART 1.0 consortium, which defined vehicle fleets for different scenarios of technology development and market adoption. NREL has determined home charger availability based on housing type and scenario. See Table I.13.1 for details.

Table I.13.1 EV and Home Charger Ownership Based on Housing Type and Scenario

Scenarios	High EV Ownership – Low Home Chargers		High EV Ownership – High Home Chargers	
Housing Type	**Multi-Unit**	**Single-Unit**	**Multi-Unit**	**Single-Unit**
EV Ownership	21%	79%	21%	79%
Home Charging	5%	61%	50%	100%

As an initial case study, the high ownership – low home chargers scenario (the one likely to result in most public charging) was run unconstrained in POLARIS and has been labeled "S0". "Unconstrained" means that vehicles have access to unlimited charging whenever and wherever they want at an infinite transfer rate (charging takes no time). This initial case is run to inform NREL's EVI-Pro [5] of the charging demand (location, time, and amount of energy charged). In turn, EVI-Pro provided POLARIS with three different Electric Vehicle Supply Equipment (EVSE) configurations. The "Medium – 100%" scenario represents a situation where the number of plugs and stations match the expected demand for charging. In the "Low – 70%" scenario, the charging capacity is 30% under the expected charging demand while in the "High – 130%" case, the charging capacity exceeds the charging demand by 30%. See Table I.13.2 for details.

Table I.13.2 EVSE Siting from EVI-Pro

Charging Supply Levels	Stations	Plugs	
		Level 2 (7 kW)	**DCFC (50 kW)**
Low – 70&	2,781	22,888	8,278
Medium – 100%	3,979	32,723	11,934
High – 130%	5,379	42,884	18,329

With the given charger configurations, six additional scenarios were run:

- High EV ownership, low home charging availability
    - Low EVSE supply (S1)
    - Medium EVSE supply (S2)
    - High EVSE supply (S3)
- High EV ownership, high home charging availability
    - Low EVSE supply (S4)
    - Medium EVSE supply (S5)
    - High EVSE supply (S6).

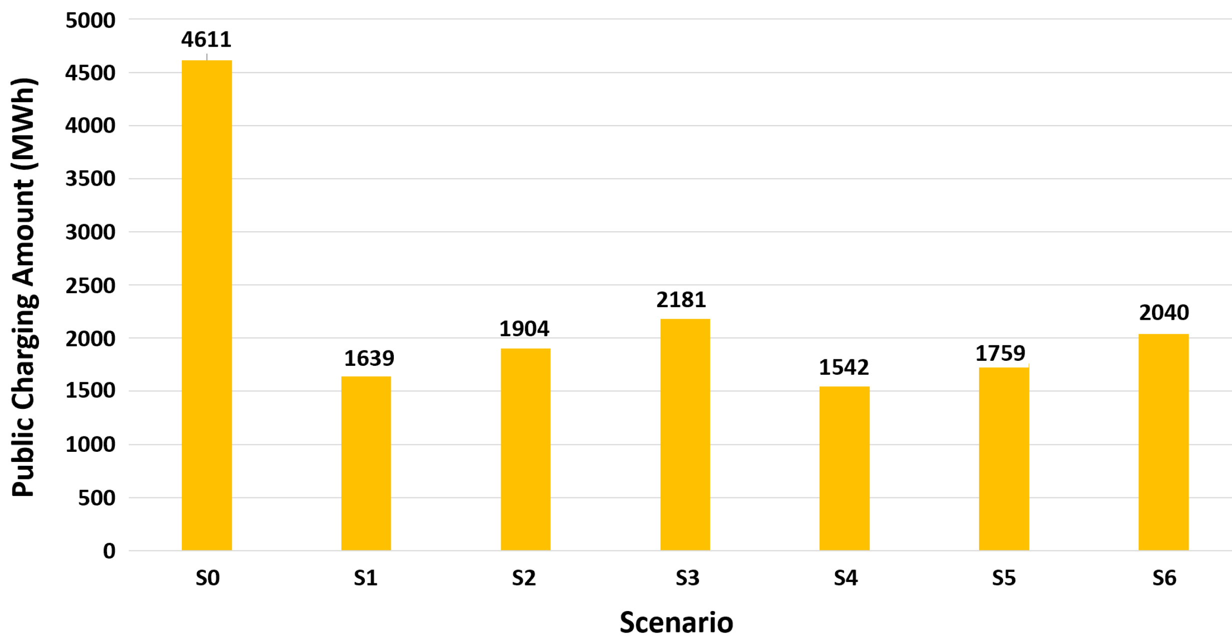

Figure I.13.3 Public charging amount by scenario. Source: ANL

Figure I.13.3 shows the charging amount per scenario in MWh. As public charging availability increases (S1 to S3, and S4 to S6), the public charging amount increases. Moreover, public charging decreases slightly due to higher home charging availability in scenarios S4 through S6 (relative to the corresponding scenarios, S1 through S3). Another interesting metric to look at is charger utilization rate, calculated as follows:

$$\frac{Charging\ Amount\ (kWh)}{Plug\ Power\ (kW) \times 24hr \times Number\ of\ Plugs}$$

As seen in Figure I.13.4, the home charger utilization rate remains relatively constant around 35%, which corresponds to a utilization of approximately eight hours. As expected, the public charging utilization rate is much lower. Moreover, the utilization rate decreases as the station availability increases.

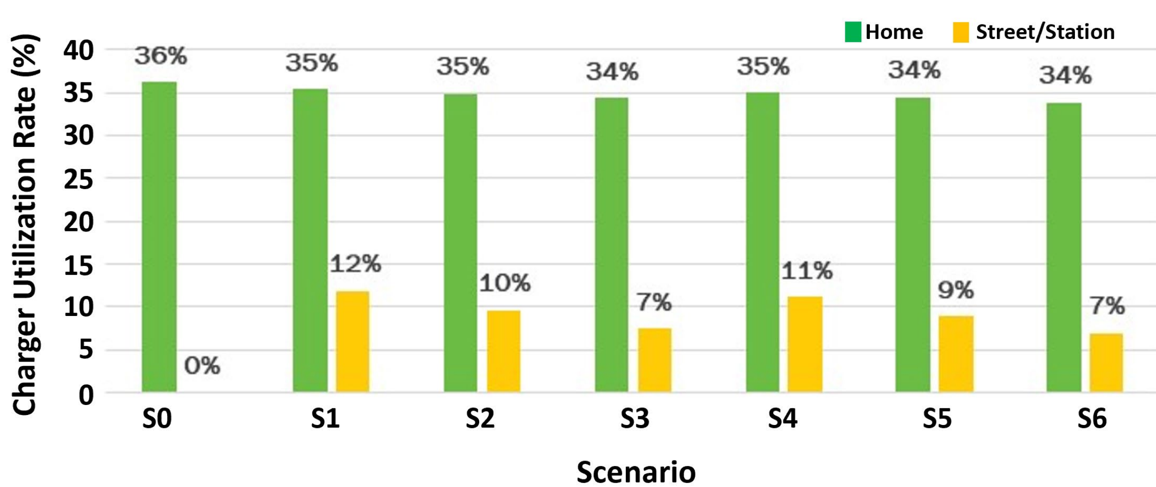

Figure I.13.4 Home and public charging amount by scenario. Source: ANL

Conclusions

This analysis has shown that:

- Based on the cost of driving for medium- and heavy-duty trucks, the share of electrified powertrains increases over time but, in all cases, a powertrain mix provides the lowest cost.
- To offset their higher cost, PHEV and BEV should be used on longer routes to benefit from their lower operating cost.
- As the availability of public charging increases, the total amount of public charging increases. However, the charger utilization rate decreases.
- Availability of home chargers reduces public charging slightly while increasing home charging.

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Acknowledgements

Major contributors not listed above include Vincent Freyermuth and Omer Verbas of Argonne, and Eric Wood and Fan Yang of the NREL.

I.14 Spatio-Temporal Analysis of TNC Effect on Transit Trips in Chicago (Argonne National Laboratory)

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Start Date: June 1, 2020 End Date: September 30, 2021
Project Funding (FY21): $150,000 DOE share: $150,000 Non-DOE share: $0

Project Introduction

This analysis was motivated by the loss of transit ridership in the Chicago area over the past several years, a trend that overlaps with the introduction of TNCs in the region. There is an apparent correlation between the two, which has led to speculation that TNCs have caused transit ridership loss. However, many other factors outside of TNC ridership could be driving transit ridership loss, including changes in populations, shifting land use patterns, transit service changes, macro-economic factors, and more. This team developed regression models for analyzing the impact of ride-sharing services on transit demand.

This work builds on the previous analysis of Ward et al. [1]. That research team analyzed the effect of TNC on transit ridership and vehicle ownership across the U.S. during the 2011–2017 period. Similar to our results, Ward et al. [1] determined that there is no effect of TNC on transit use on average. However, they did suggest that there are local effects in the areas with both significant transit ridership and high income. Ward et al. [2] and Ward et al. [3] analyzed 2005–2015 data and found out that vehicle registrations declined by 3% on average as a result of TNC entering the transportation market.

In this project TNC and transit data collected in Chicago at a monthly time resolution was analyzed using community area (CA) as spatial units of analysis. The analysis of non-overlapping spatial areal units has been analyzed in statistics, agriculture, and epidemiology [4], [5], [6],[7].

Objectives

The main objective of this study was to analyze the impact of ride-sharing services on transit demand. A methodological framework was developed, using regression models, which allows for the disaggregate analysis of long-term transit ridership data. Data from multiple sources, including transit boardings and alightings and TNC demand in the City of Chicago, were used. The model developed allowed for disaggregate analysis of long-term transit ridership data from Chicago between 2010 and 2020, before and after the introduction of TNC services, along with TNC trip patterns to determine relationships between TNC ridership and transit ridership in similar parts of the city.

Approach

Multiple data sources were used in the analysis. The TNC open data provided by the city of Chicago contains the number of trips, on an hourly basis, between each origin/destination CA. Each trip record in the TNC open data has information regarding trip origin and destination, date, and other attributes of the trip, such as fare, distance, and whether it was a shared ride. The resulting dataset had 794, 179 rows and ranged from 2018-11-01 to 2020-02-29.

The transit boarding and alighting data were obtained from the Chicago Transportation Authority. The estimates are based on the Automatic Passenger Count data, fare card transaction data, and internal Chicago Transportation Authority modeling and were obtained through a Non-Disclosure Agreement. The data was further processed to remove extreme data and it was aggregated spatially at the CA level. The analysis period includes the TNC data period, and the counts were aggregated by month for bus service and rail service (L-System) independently.

In addition to the TNC and transit data, a time-dependent dynamic traffic assignment router is used to provide estimates of cost and level of service variables across different modes [8]. This router is part of POLARIS, a large-scale agent-based model that relies on transportation demand and supply models to synthesize and simulate person and freight travel across large regions such as the Chicago Metropolitan Area [9]. Five random location points within each CA were selected, and the router was estimated for the OD matrix of the study area (corresponding to 77 CAs). Measures such as travel time, wait time, and monetary cost were estimated for different modes, including walking, biking, bus, rail, car, and TNC.

We used a model proposed by Bernardinelli et al. [10], which represents the spatio-temporal pattern in the mean response with spatially varying linear time trends. We assume that the data is Gaussian. The model estimates autocorrelated linear time trends for each CA (corresponding to the areal unit), which is appropriate if the goal of the analysis is to estimate which areas are exhibiting increasing or decreasing (linear) trends in the response over time.

Results

The model, with y as TNC counts (Poisson) and predictor variables, bus and rail average daily counts on log-scale, is shown below:

The main highlights from the model are:

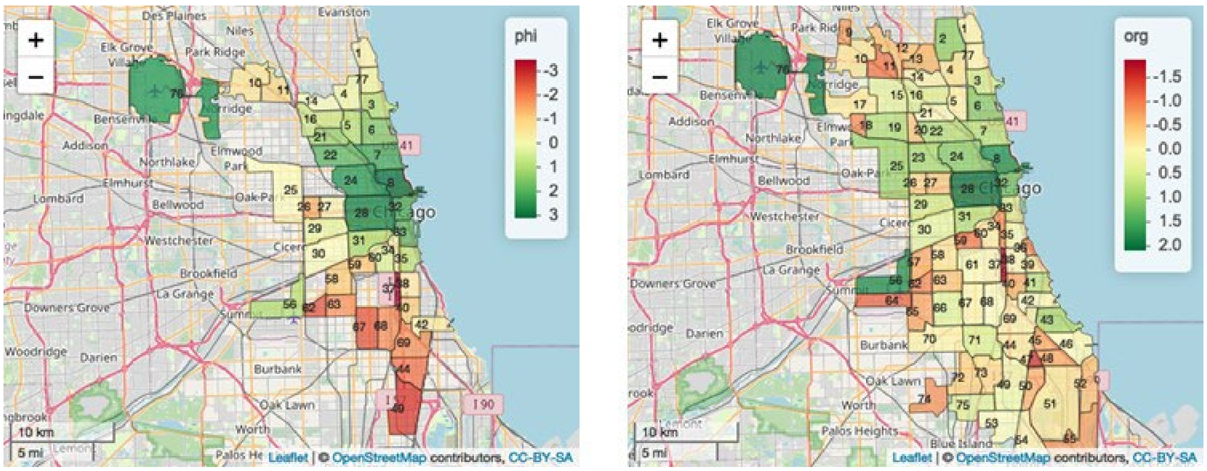
- Bus and rail move in the same direction as TNC
- When bus goes up 1% TNC goes up 0.23%
- When rail goes up 1% TNC goes up 0.39%
- Overall, the time trend is slightly negative; α=-0.08
- Tau2.int, which is spatial random effect variance (τ_{int}^2), is large (a large fraction of variance is not explained by variance in bus or rail)

Table I.14.1 TNC Count Model

	Median	2.5%	97.5%
(Intercept)	0.8069	0.1768	1.4466
log(bus)	0.2332	0.1837	0.2796
log(rail)	0.3932	0.3489	0.4402
Alpha	-0.0847	-0.1069	-0.0605
tau2.int	3.3423	2.2283	5.3536
tau2.slo	0.0406	0.0237	0.0712
rho.int	0.7319	0.3979	0.9496
rho.slo	0.4749	0.1174	0.8667

- tau2.slo, which is temporal trend variance (τ_{slo}^2), is low, which corresponds to our initial observation that there is not much change in data over time (for the observed time period)
- rho.int, which is the strength of the spatial correlation, is high ($\rho_{int} = 0.73$)
- There is no local effect on the trend, as most of the local effect coefficients δ are around 0.

Also, we can look at the random spatial effects ϕ_k (correlations), not captured by the main effects, shown in Figure I.14.1 (a). We can see that spatial effect is stronger in the central and northern parts of the city. This means that both bus and rail ridership are highly correlated in these areas. Another hypothesis considered in this analysis is that temporal analysis of flows between CAs will lead to discovering effects of specific areas. We modeled the flows using a gravity model, which is a class of log-linear regression that has been previously shown to be effective in traffic flows modeling [11], [12], [13]. Specifically, we used the observed TNC origin and destination flows as our observed data set and used the POLARIS-estimated area-to-area generalized travel cost as our inputs. Results shows a large variation on the random effect of a destination on the number of the TNC trips while controlling for generalized cost and TNC. Thus, we expect the random effect to be of non-trivial size for each of the destinations, as shown in Figure I.1.1 (b).



(a) (b)

Figure I.14.1 Random spatial effects of (a) trip counts and (b) trip flow. Source: ANL

Conclusions

The project team developed regression models for analyzing the impact of ride-sharing services on transit demand using data from multiple sources, including transit boardings and alightings and TNC demand in the City of Chicago. The models allowed for disaggregate analysis of long-term transit ridership data from Chicago between 2010 and 2020, before and after the introduction of TNC services, along with TNC trip patterns to determine relationships between TNC ridership and transit ridership for similar areas.

The main results suggest no significant change in transit ridership data over time for the observed period. Moreover, neither global (region overall) nor local (area-specific) trend coefficients were found to be significant, meaning there is not enough evidence in the data to suggest that there is any time trend in the TNC ridership counts. The strength of the spatial correlation is high, which is likely explained by key unobserved variables. For example, the high and low-income areas are clustered, and thus the usage of the TNC is clustered as well. In addition, an origin-destination flow temporal analysis to discover the effects of specific areas was developed. The results confirmed the finding of the analysis performed using only out-flow data. Adding the control for the generalized travel cost (as estimated by the POLARIS router) did not reduce the size of the random effects of each of the areas, which tells us that the generalized cost did not have explanatory power for explaining the TNC counts.

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I.15 Off-Road Vehicle Energy-Saving Potential (Argonne National Laboratory)

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Start Date: October 1, 2020 End Date: September 30, 2021
Project Funding (FY20-FY21): $150,000 DOE share: $150,000 Non-DOE share: $0

Project Introduction

The DOE VTO has played a critical role in enabling electrification and reducing fuel consumption in the automotive sector. However, the off-road vehicle sector accounts for 8% of transportation fuel, and that share is likely to increase over time as on-road vehicles move towards electrification. DOE can play a key role in the off-road vehicle market by providing tools that can be used by academia and the industry to evaluate the impact of advanced technologies. The need for a pre-competitive simulation tool was also identified during a 2019 DOE-led workshop at Argonne that included OEMs and suppliers to this market.

The objectives of this project were to:

- Provide a pre-competitive simulation platform to OEMs, suppliers and academia to evaluate technologies
- Quantify the potential fuel savings of selected applications resulting from electrification
- Facilitate collaboration within the industry.

While Autonomie has traditionally been used for on-road vehicles, we are now developing features, models, and processes to facilitate the modeling of off-road vehicles. This work focuses on wheel loaders and excavators with the intention of building model capabilities that could be used to simulate a wide variety of off-road applications.

Approach

Currently, Autonomie [1] is centered on models of on-road vehicle powertrains that move a vehicle forward along a defined vehicle speed profile. This project expands those capabilities by adding models that represent the multiple functions that off-road vehicles can perform using the power generated by the powertrain. More specifically, we are adding fluid power system models to simulate the duty cycles of hydraulic systems used to extend arms, rotate cabins, and extend buckets. The project focuses on new vehicle control and powertrain architectures that can provide fuel savings over current architectures. We partnered with the University of Helsinki [2],[3] which has a long history of modeling off-road applications, to integrate models into Autonomie. The construction and agriculture markets are respectively the number 1 and number 2 energy consuming markets in off-road vehicle applications. Within the construction market, excavators and wheel loaders are respectively the number 1 and number 2 biggest energy consumers. In this project, we model excavators and wheel loaders as a starting point towards developing off-road modeling capabilities in Autonomie.

Duty cycle

While the passenger car market is split into defined categories (i.e., compact, SUV, pickup truck, etc.), the off-road vehicle market is loosely defined, with each OEM defining categories based on its own offerings, and while standardized drive cycles exist to evaluate the fuel consumption of passenger cars, no standardized vehicle level duty cycles exist to define off-road applications. In addition, the multitude of moving parts makes it difficult to define a complete vehicle level cycle. The EPA defines engine-only duty cycles for wheel loaders, excavators, and other applications, but does not specify how the engine power is used in the vehicle [4]. The Japan Construction Mechanization Association [5] provides a detailed outline of an excavator duty cycle that can be used to determine fuel consumption. Working with an OEM that has run and collected data on such a test to validate the duty cycle and component behaviors would be a possible next step for this project.

Through a literature review [6],[7],[8], a representative duty cycle was identified for the excavator. An excavator duty cycle can be broken down into four independent motions: (1) arm motion, (2) bucket motion, (3) boom motion, and (4) cabin motion.

A duty cycle can be identified for each independent motion for a typical excavator job: loading up material from one location and dumping it at another location. The actual motion of the vehicle itself is not considered in this study, as typically the excavator is not moving, and little energy is spent in vehicle motion.

Figure I.15.1 shows the duty cycle as a function of time, and Figure I.15.2 shows the total duty cycle power demand repeated over time.

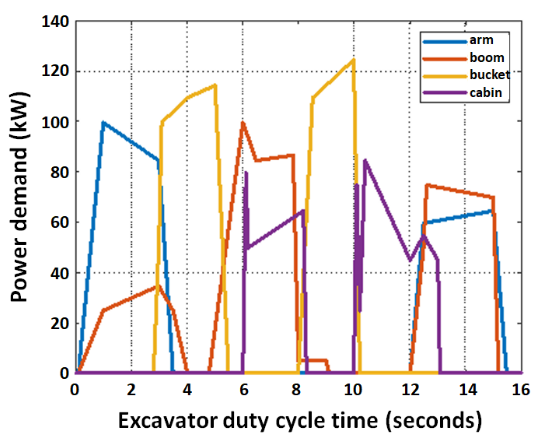

Figure I.15.1 Power demand for duty cycle. Source: ANL

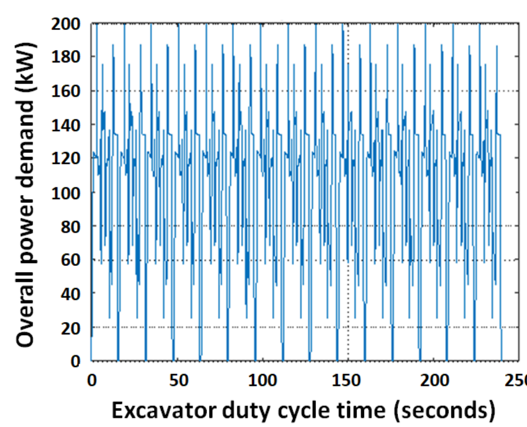

Figure I.15.2 Overall power demand for duty cycle. Source: ANL

While there is no standardized and regulatory vehicle level duty cycle for wheel loader and off-road machines in general, a wheel loader duty cycle commonly used to assess vehicle level fuel consumption is the V-cycle, which describes the repetitive back and forth vehicle motion carried out as the vehicle loads material in the bucket and dumps it in a truck. A synthetized vehicle speed profile for the V-cycle is shown in Figure I.15.3.

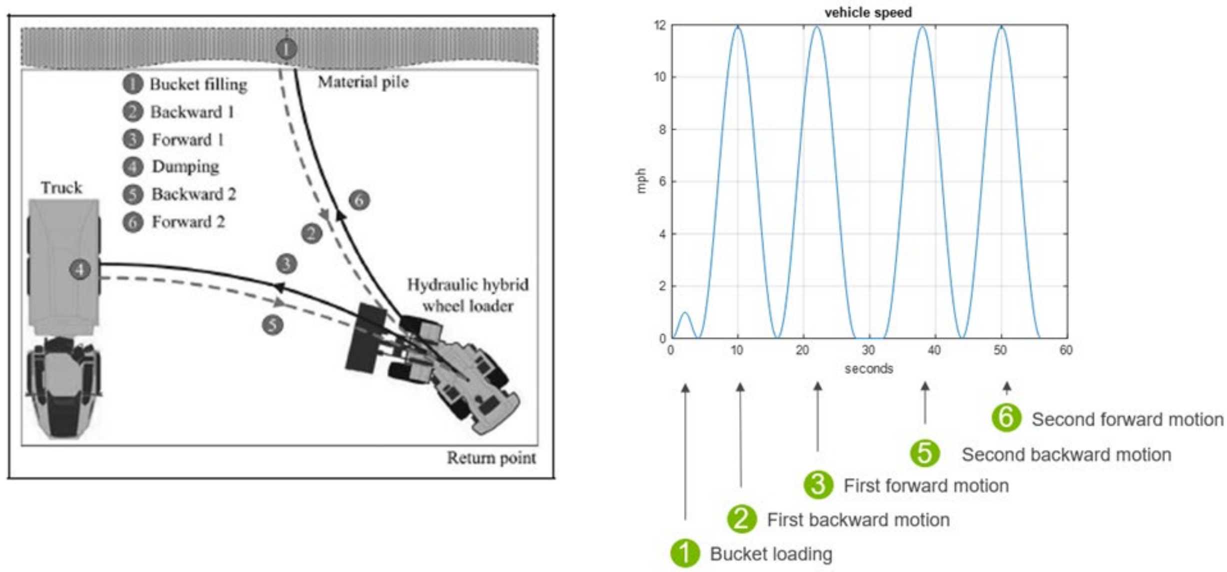

Figure I.15.3 V-cycle vehicle speed profile. Source: ANL

Modeling

Excavators

Modeling off-road vehicles in Autonomie poses a few challenges. A primary input to Autonomie is a vehicle speed profile that serves as the base to determine powertrain power demand. In the case of an excavator, the vehicle is at a standstill while vehicle functions are executed by an arm, a boom, a bucket, and a rotating cabin. A baseline model of the excavator was implemented in Autonomie and exercised over the selected duty cycle. Hydraulic components such as hydraulic cylinders, valves, pumps, and motors were also implemented in Autonomie. The driver model was modified as the driver does not just follow a vehicle speed trace but also runs stationary functions. The model uses a 9.3 L diesel engine (232 kW) and a centralized hydraulic system.

Engine power, speed and torque to support the hydraulic functions are shown in Figure I.15.4. The engine power closely follows the hydraulic power. The current engine control in Autonomie, based primarily on how passenger car engines behave, shows relatively high engine speed fluctuations as it operates the engine at its most efficient point for a given power demand in order to minimize fuel consumption. Engine behavior in off-road machinery is such that the speed remains relatively constant, and the torque varies to match the power demand. Working with OEMs and having access to field data would be necessary to validate and adjust the engine speed control accordingly.

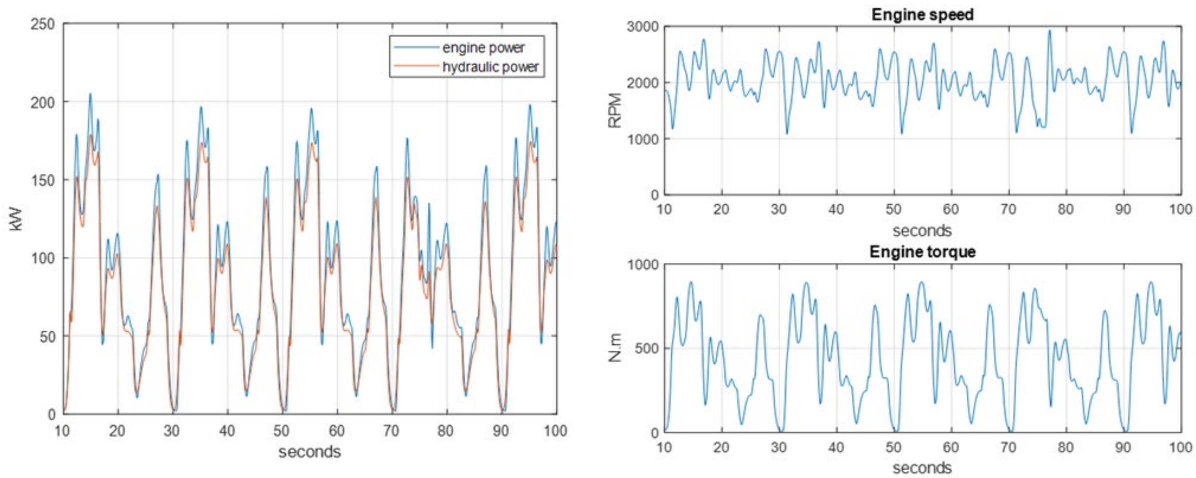

Figure I.15.4 Engine power, torque, and speed. Source: ANL

The excavator was hybridized by electrifying the cabin rotation. The hydraulic system used for the cabin rotation in the conventional system is replaced by an electric machine and a 4 kWh 540V li-ion battery. When the cabin slows down, regenerative energy is captured through the electric motor and stored in the battery. Figure I.15.5. highlights the power of the four hydraulic functions. The amount of energy recovered remains relatively small compared to the overall energy spent, and the fuel savings in this example is approximately 5%.

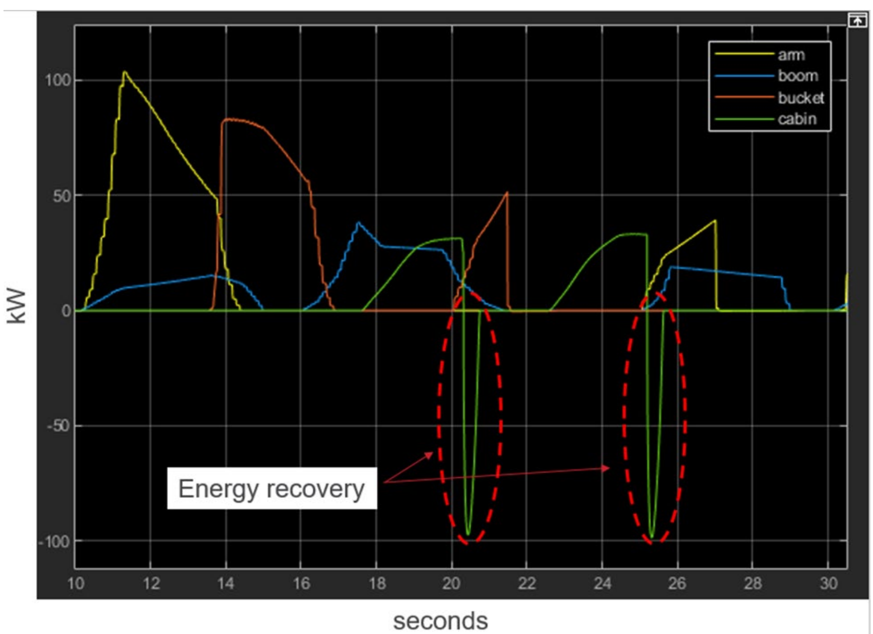

Figure I.15.5 Arm, boom, bucket, and cabin power profile in the hybrid excavator. Source: ANL

Wheel loaders

Autonomie was originally designed to move a vehicle along a predefined speed profile without obstacles. In the case of the wheel loader, the modeling of the penetration of the bucket into a pile of material is of particular interest as it is akin to modeling a vehicle running into an obstacle, a case study that never occurs in the modeling of light-, medium-, and heavy-duty on-road vehicles. This power required to load up the bucket could not be accounted for in the way the driver model was originally set up and required modifications. The extra loading force itself is modeled in the vehicle loss model where other losses are accounted for (i.e., tires, grade, aerodynamics).

The hydraulic component models used to represent the lift and tilt motion are similar to the hydraulic components used in the excavator model. The conventional powertrain uses an automatic transmission with a torque converter illustrated in Figure I.15.6. The hybrid version developed in this project replaces the torque converter with an electric machine geared to the transmission input as well as a clutch to mechanically connect the engine to the gearbox. We used a high voltage li-ion battery as a storage device.

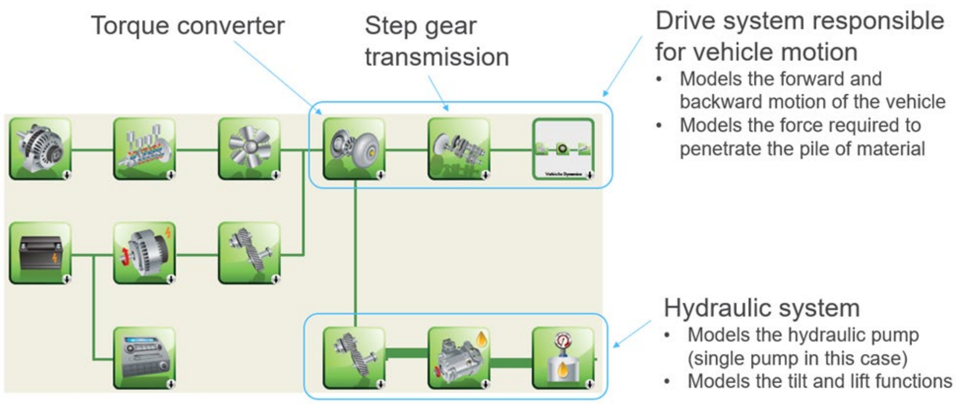

Figure I.15.6 Wheel loader schematic in Autonomie. Source: ANL

The combination of reduction in torque converter losses, the capture of regeneration energy, and the change in engine operations provides a 15% reduction in fuel consumption over the cycle. Figure I.15.7. highlights how the hybrid powertrain engine operates in an area of higher engine efficiency compared to the conventional powertrain.

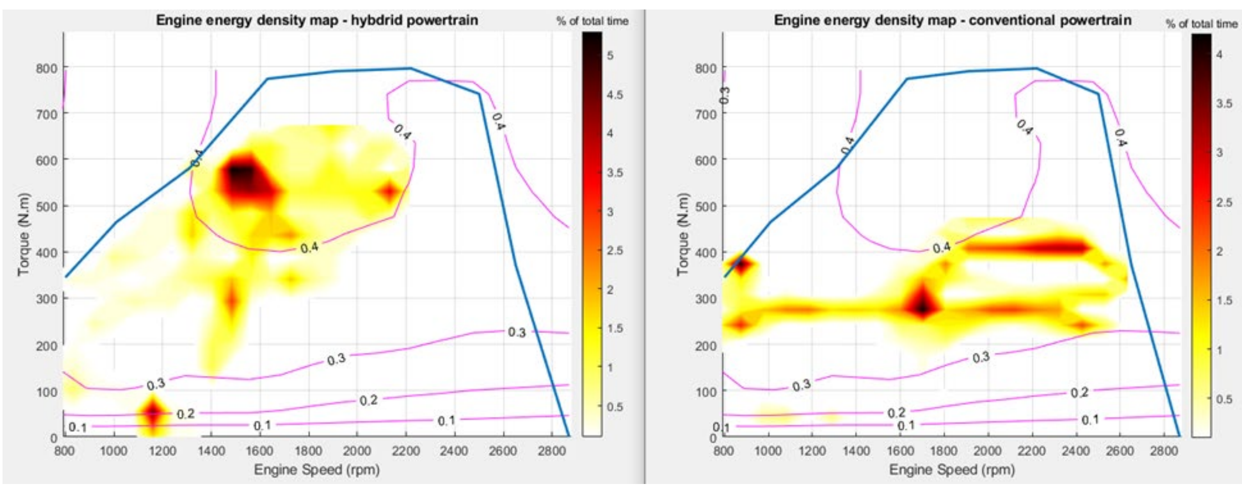

Figure I.15.7 Wheel loader engine operations. Source: ANL

Conclusions

In this project we developed representative Autonomie models for an excavator and a wheel loader. For each machine we developed a baseline version (i.e., conventional powertrain) as well as a hybrid version that provides fuel savings compared to the baseline. Hydraulic models were developed and integrated into Autonomie to support the modeling of the working functions of the machines. Those models include hydraulic pump, valve, actuator, and cylinder models.

Early in the project we presented our research at the Center for Compact and Efficient Fluid Power - CCEFP 2020 Summit. While our results were limited at the time, feedback was positive, and participants highlighted the benefit of a public tool to quantify the benefits of electrification.

Wheel loaders and excavators cover a very wide range of functions, duty cycles and power requirements, and the lack of standards makes it difficult to accurately represent these machines. The lack of publicly available data is such that models cannot be easily validated. Engagement with the industry would be required to continue this effort and to increase the level of fidelity in the models and their predictions.

Future work could focus on other ways to reduce energy consumption. While an electrical system may not always be able to replace a hydraulic system, decoupling the hydraulic system from the engine offers opportunities for further energy savings. For example, a hydraulic pump that is continuously tied to the engine will spin and generate losses even when it does not need to generate hydraulic power. Also, fuel cell battery hybrid systems could replace engine-based powertrains in large machines where full electrification may not be feasible due to the large energy requirement.

Key Publications

Freyermuth, Vincent, Vijayagopal, Ram, and Rousseau, Aymeric. 2021. "Off-Road Vehicle Energy-Saving Potential". United States. https://doi.org/10.2172/1818063. https://www.osti.gov/servlets/purl/1818063.

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I.16 Electric Vehicles at Scale – Phase II. Distribution System Analysis (Pacific Northwest National Laboratory)

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Start Date: June 1, 2020 End Date: December 31, 2021

Project Funding (Initial): $550,000	DOE share: $550,000	Non-DOE share: $0
Project Funding (FY20–FY21): $0	DOE share: $0	Non-DOE share: $0
Total Expected Project Funding: $550,00	DOE share: $550,000	Non-DOE share: $0

Project Introduction

Over the last decade the use of EVs in the U.S. has grown significantly. Accompanying the growing numbers of EVs on the roads is growth in electricity demand to meet EV charging needs, calling public attention to electricity delivery capacity constraints inherent in the US's aging grid infrastructure. If these supply-side limitations are not managed effectively, the U.S. transition from fossil-fueled vehicles to clean electric resources could be disrupted.

This project has developed a methodology to address the following four key questions of interest to DOE related to the impacts that EVs are likely to have across the energy grid distribution systems.

1. When (i.e., which year), where, and how many EVs will be adopted in the U.S.?
2. How will EVs in the U.S. be charged?
3. Given some prospective answers to the above question, what would be the EV hosting capability of a given distribution system circuit?
4. How could one expand the hosting capability to accommodate more EVs and what would be the potential measures and cost?

This project is a continuation of the previously completed Phase I project, which focused on the bulk power system [1].

Objectives

This project has three objectives:

- **High-spatial resolution EV Adoption Modeling**: This project establishes a new EV adoption modeling methodology, at the household level (i.e., unique street addresses), for estimating the likelihood of EV adoption. This methodology should estimate the likelihood of EVs being charged at a neighborhood level. The spatial results of projected EV adoptions are then referred to a power flow simulation capability which estimates potential condition-specific power flow violation problems of the distribution system at the circuit/feeder level.

- **Development of tools for estimating EV hosting capabilities**: The project has developed a methodology and programming scripts for estimating EV hosting capabilities at the circuit feeder level to aid distribution system planners perform capacity forecasts.

- **Testing of methodology for a Distribution Feeder of SCE**: In collaboration with Southern California Edison (SCE), PNNL tested the methodologies and tools described above on a single distribution system circuit selected by SCE engineers.

Approach

Two distinct modeling approaches have been developed or applied:

- **EV adoption model**: PNNL used a Bass market adoption model framework and fitted it with highly spatially disaggregated data such that EV adoption could be estimated at the street address level of granularity. Model inputs included EV registration data, household income data, home assessment data, and (if applicable) incentive information. The output of the model is probabilities of EV adoption by address within any given geographic domain (again, down to as specific as the street address level).

- The EV adoption impact analysis is based on an established **AC power flow simulation model (GridLAB-D)** that simulates the 3-phase power flow in a distribution system given load characteristics. The EV adoption model transferred data to the GridLAB-D model in order to identify any potential violations of the American National Standards Institute standard for reliable and safe distribution system operations.

PNNL has demonstrated the two methodologies developed for a distribution feeder in SCE's service area and discussed the results with the utility.

The overall methodology is shown in Figure I.16.1.

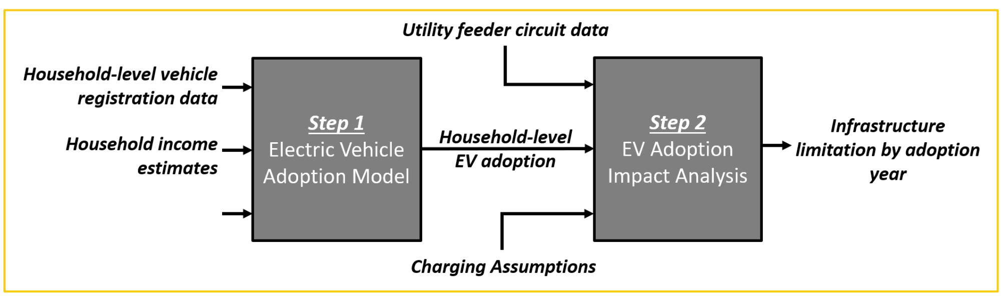

Figure I.16.1 EV Adoption modeling approach. Source: PNNL

Results

The EV adoption model was applied to an SCE distribution feeder with 2381 residential homes. The aggregated EV adoption for this area is show in Figure I.16.2. The disaggregation into 3 groups represent the different EV classes, with Group 1: long-range EV (similar to Tesla); Group 2: short-range EV (similar to Nissan Leaf); Group 3: Plug-in hybrid.

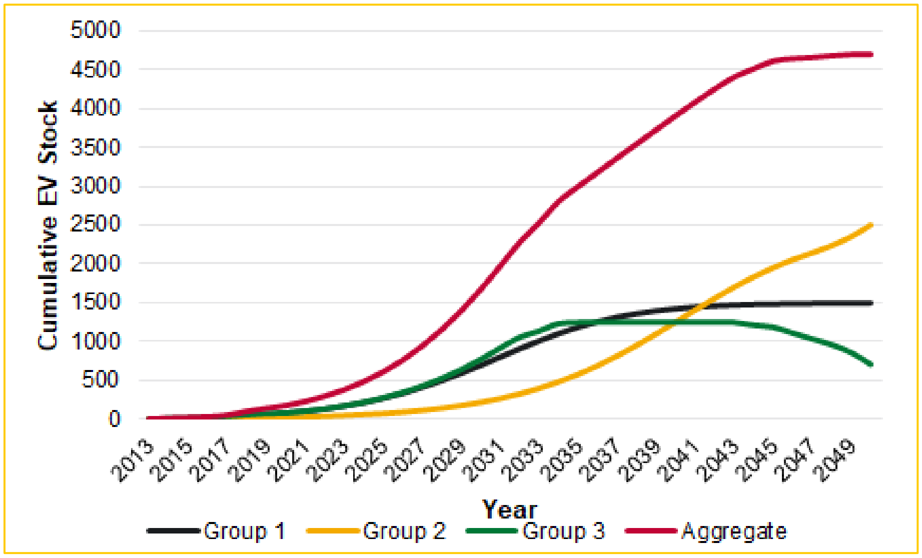

Figure I.16.2 Cumulative EV adoption. Source: PNNL

Cumulative EV Adoption in SCE feeder by group of EV and year. The actual placement of EVs across addresses is shown in Figure I.16.3 below. The placement represents a sample of a statistical distribution of individual homes adopting EVs based on the aggregated EV fleet as projected in Figure I.16.2 above.

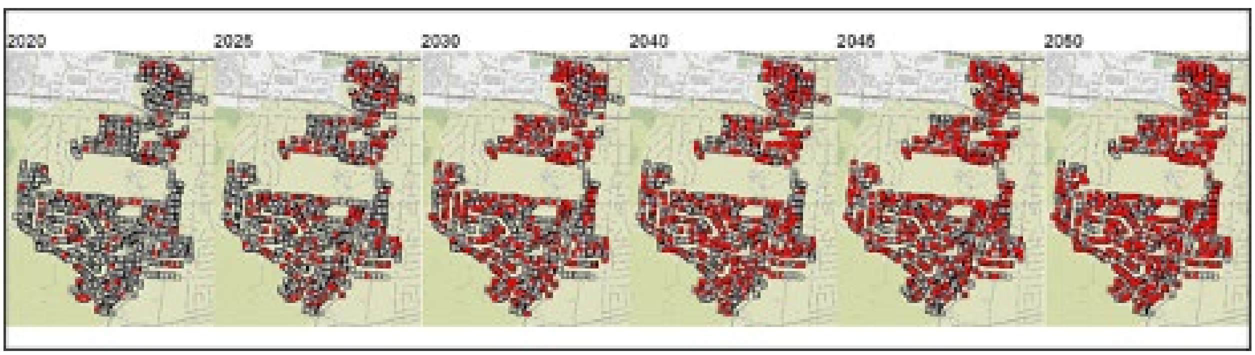

Figure I.16.3 Placement of EVs across Addresses. Source: PNNL

An example of the EV impacts analysis is shown in Figure I.16.4. The y-axis expresses the exceedance of the rated capacity of a secondary transformer that services 5–10 homes. The figure shows the number of service transformers that need to be upgraded to accommodate the increased power demands due to EV charging. If Smart Charging Management (SCM) strategies are applied, the transformer upgrading can be deferred. PNNL estimated the benefit associated with the deferment of transformer upgrading.

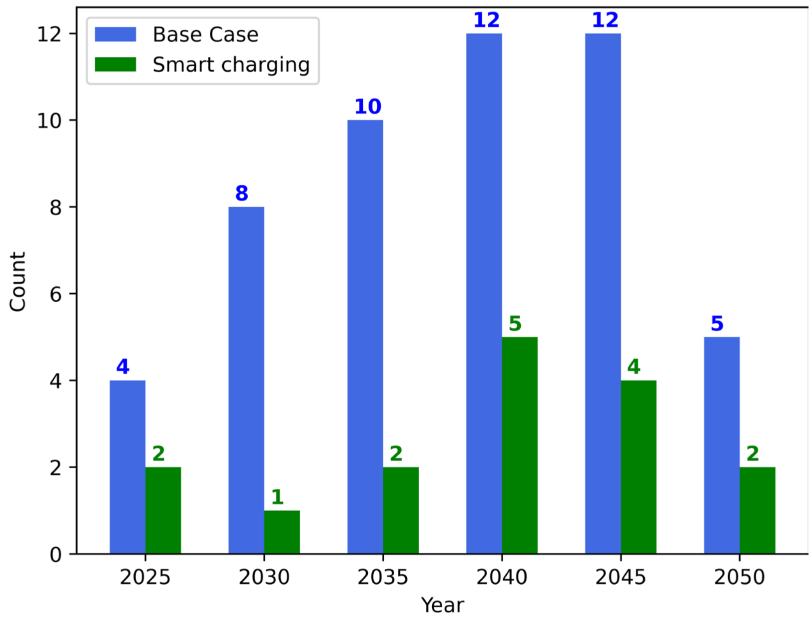

Figure I.16.4 Transformer Upgrade Plan for Every 5 Years with and without SCM. The "Count" values refer to the number of service transformers requiring upgrade in order to accommodate increased power demands that result from EV charging. Source PNNL

Conclusions

The key outcomes of this project were two independent capabilities, including (1) providing future year projections of LDV EV adoption at various levels of geographic aggregation down to the address level, and (2) a set of scripts and routines that enable the distribution system power flow studies to be carried out which estimate the hosting capability of a feeder circuit under a set of EV adoption assumptions. While the audience for this new analytics capability was originally assumed to be distribution system planning engineers, the EV adoption model also generated interest among community energy leaders and transportation planners, both of whom are interested in assessing the needs for public charging infrastructure that will meet the future transportation needs of communities (i.e., at the city and county levels). Particularly, the socioeconomic characterization and transparency of the adoption model has drawn the attention of community leaders, who can use the model to analyze how future investment in public charging infrastructure can benefit underserved populations, including via targeted placement of public infrastructure that ensures the achievement of equity goals and objectives.

EV adoption model. The adoption model estimates annual sales figures for three groups of EVs (i.e., long-range EVs, short-range EVs, and PHEVs) in a certain geographic footprint. The footprint can be as large as a state and as small as the geographic boundary of a distribution system feeder circuit. The inputs to the model are (1) vehicle registration data, by year, (2) household income, by census block, and (3) housing assessed value and characteristics in single versus multi-family homes, by address. Given these input data, the EV adoption model estimates the annual adoption of EVs by groups within the given footprint, and the propensity for adoption each year by address.

This new capability can thereby be used to:

- Study the locational aspects of how EV adoption might occur in a community without any policy intervention and how different socioeconomic groups might be affected; and
- Design incentives, such as free electricity, buy-downs through rebate programs, or providing access such as public charging stations to target certain populations.

Hosting capability estimations. This estimation uses a sequence of power flow simulations to model the operations of the electric distribution system under the new (forecast) EV load conditions. PNNL's GridLab-D was used to demonstrate the power flow simulations, with the model fed by new EV loads as provided statistically by the EV Adoption Model (in this case, propensity of EV adoption by address). The estimation results allow planning engineers to set a risk threshold that characterizes the risk exposure of future EV loads exceeding any operating conditions. The outputs of hosting capability estimations are (1) an estimate of the maximum number of EVs that can be accommodated in a particular footprint that also specifies in which future year that limit is expected to be reached given an adoption rate; and (2) the specific asset/component in the distribution circuit that is inadequate or deficient for safe operation and thus needs to be updated to meet the adoption rate. An engineer can then explore upgrade strategies to address the limiting set of assets or even control strategies for EV load to remediate the limiting condition.

Demonstration of the new capabilities. PNNL demonstrated the capabilities on a single feeder in the SCE service area as an illustrative example. The research team used California Department of Motor Vehicle registration data, home value assessments and house characterization, and household income data. With these inputs, a projection of personally owned light-duty EV market adoption, by address, was performed. The results were then fed into a power flow model to simulate potential violations against American National Standards Institute standards and engineering guidelines. The power modeling can identify the location of each violation and its time and frequency of occurrence.

With these outputs, the distribution planner is able to determine EV hosting capabilities and distribution upgrade strategies if more EVs are expected in the future. The combination of the EV forecasting and the power flow modeling tools provides all of the analytical instruments that distribution system engineers would need to analyze impacts related to a growing EV fleet in the distribution system. PNNL also demonstrated how to estimate the upgrade deferral that would result from the application of SCM as well as the other potential benefits of SCM such as mitigating voltage violations.

Key Publications

Sridhar S, Holland C, Singhal A, Kintner-Meyer M, Wolf Katherine, "Distribution System Planning for Growth in Residential Electric Vehicle Adoption." IEEE PES GEM 2022. Conference paper.

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I.17 Analysis of Electric Heavy-Duty Driving and Infrastructure Requirements Within a Regional Area (Electric Power Research Institute)

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Start Date: October 1, 2020	End Date: December 31, 2021	
Project Funding (Initial): $193,755	DOE share: $144,186	Non-DOE share: $19,569
Project Funding (FY20-FY21): $251,013	DOE share: $225,643	Non-DOE share: $25,370
Total Expected Project Funding: $444,768	DOE share: $399,829	Non-DOE share: $44,939

Project Introduction

This project seeks to analyze heavy-duty freight movement and to estimate the transmission and distribution impacts of electrification of these vehicles. Currently Class 7 and 8 electric tractor trucks are available in prototype form, with commercial models expected to be available in the near future. These tractors can be connected to existing trailers and could quickly become part of the freight transportation system. A key question is the potential difficulty and cost of installing infrastructure to recharge these vehicles, which may require "slow" charging (up to 20–100kW per plug) to charge overnight or "fast" charging solutions, potentially 1+megawatts per plug for en-route extreme fast charging. Clusters of truck chargers at warehouses or truck stops may require tens or hundreds of megawatts per site, which will require significant service expansion and upgrades to electricity distribution systems.

Objectives

The objective of this project is to help developers, utilities and stakeholders better understand the key factors, opportunities and challenges associated with aligning heavy duty electrification needs with optimized least-cost grid solutions that benefit all parties, from developers, to utilities, and society overall. This objective will be accomplished by leveraging cutting-edge electrification and grid analytics to demonstrate new techniques to characterize electrification needs, align the need with the existing grid capacity, assess various electrification solution options where capacity is not available, and optimize for least-cost and reliability. This project will identify dominant cost factors and sensitivities associated with the electrical system reinforcement costs needed to serve these demands, which is a critical first step towards determining least-cost solutions to supply the energy needs of an electrified heavy duty transportation sector while optimizing the benefits through lower utility rates and decreased carbon emissions.

Approach

The planned analysis includes the following sub-steps:

Model heavy-duty freight transportation within a limited region – This step is being performed by NREL with input from the Electric Power Research Institute (EPRI). Data from the NREL Fleet DNA database, the FAF, and other sources will be used to model freight transportation within a representative, but limited region. Previous analyses sponsored by DOE VTO are being leveraged to estimate charging infrastructure requirements and charging loads for depot or en-route charging of Class 7 and 8 electric tractor trucks. The analysis is occurring within the service territories of three utilities in the mountain west/southwest region, Xcel Energy (Colorado), Salt River Project (Arizona), and Tri-State (Wyoming, Colorado, Nebraska, and New Mexico). This area has a large population, has a significant amount of freight flow in, out, and through the region, and has relatively isolated cities so that an analysis boundary can be defined.

Sample sites for significant charging loads – The transportation modeling has been used to identify two (2) types of sites for charging loads; warehouses/distribution centers (depot charging) and truck stops (en-route charging). Warehouses and distribution centers will be potential sites for overnight or off-duty charging, which has longer duration and lower power levels. Truck stops will be sites for higher-power charging in the middle of a freight trip. A sample of three (3) specific physical sites has been selected and load shapes have been estimated from the transportation modeling representing various fleet charging scenarios.

Quantify the grid impacts, infrastructure needs and costs to accommodate these transportation loads – Due to the high load density of these new charging facilities, most distribution and sub-transmission systems are ill-equipped to support such increased demand at service points where these types of loads (truck stops and warehouses/distribution centers) are typically connected. Grid conductor and transformer thermal capacity ratings and voltage limits could easily be exceeded unless the proper analytics are performed to assess the grid impacts and evaluate potential solutions. EPRI has developed tools for performing such analyses—Distribution Resource Integration and Value Estimation, or DRIVE, and the Transmission Hosting Capacity Tool—which will be leveraged to efficiently perform this analysis. While these tools have traditionally been used for assessing generation impacts, these tools are also well-suited for adaptation to consider charging loads as well.

The identified charging sites have been mapped to the existing electrical system and appropriate expansion needs will be identified based on system models and guidance from participating utility partners. Capital and operating costs associated with each option will be determined in relation to different levels of electric truck in-use fleet shares. This is important since low shares may not require upgrades, but high shares will likely require significant upgrades, including transformers and wire upgrades – and potentially even substations. The tipping point in electric truck deployment that triggers upgrades is site-specific, but no analyses currently exist to inform on underlying factors, as cost models based on small pilot projects do not represent the non-linearities of scaling up to fleet-level or regional coverage. At the end of this step, the challenges, and costs of expanding electricity service at the proposed sites should be known and can inform future charging system and utility designs to support the electrification of this segment of transportation.

Evaluate modified charging and localized storage to support least-cost expansion alternatives – Flexibility in the design and operation of charging infrastructure offers the potential to optimize the relationship between the transportation and electrical systems, benefiting all stakeholders. Siting of local energy sources or storage can also provide additional design and operational flexibilities that may offer the ability to further optimize these systems. As appropriate for each type of heavy-duty charging site, profiles representing alternative charging will be derived and evaluated against time-based capacity calculations for each system expansion design. Leveraging tools such as EPRI's Distributed Energy Resources Value Estimation Tool, or DER-VET, the application of optimally sized energy storage to further modify the demand profiles and reduce overall costs will also be evaluated. The outcome of this effort will be an increased understanding of how the system charging design, electric system expansions options, and distributed energy resources can be leveraged together to optimize a least-cost solution that benefits all stakeholders.

Results

This project is approaching the end of budget period 1, with two budget periods to go. Relative to the approach discussed above, the freight modeling and site selection has been completed, and quantification of grid impacts has begun. The grid impacts modeling performed so far is using simplified tools to confirm that the data is complete and appropriate for detailed analysis next year. Sample output is presented below, showing line rating and line loading (without vehicle charging) for a sample circuit. In the next year, we anticipate completing this grid impacts analysis, calculating total costs, and evaluating alternative approaches to achieve lower costs.

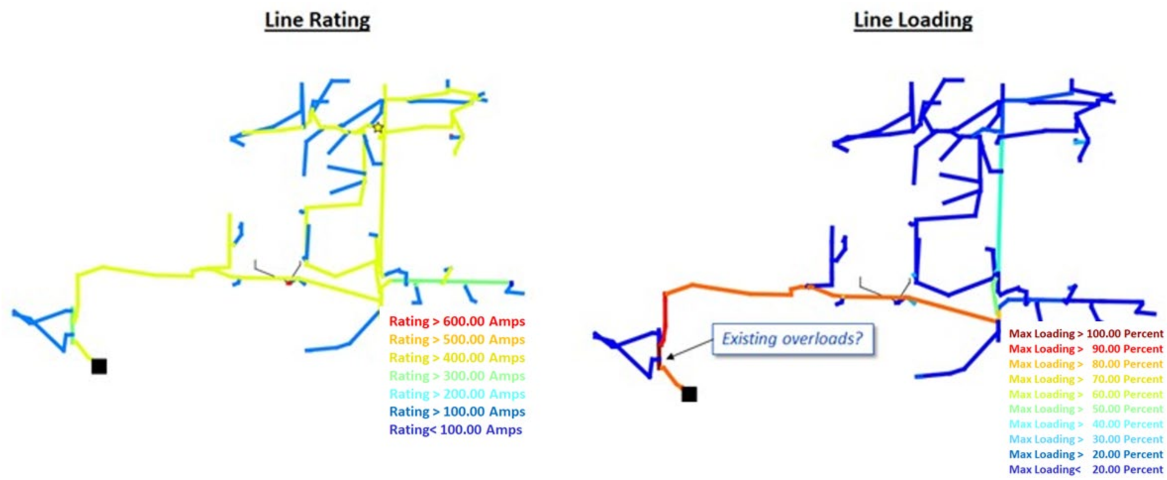

Figure I.17.1 Sample output from DRIVE modeling of line rating and line loading. Source: EPRI

Conclusions

This project is on target to meet the technical objectives for the year and, once complete, should provide interesting and valuable insights for a variety of stakeholders into the cost of heavy-duty electric vehicle charging infrastructure, including key factors, opportunities, and challenges associated with aligning heavy duty electrification needs with optimized least-cost grid solutions.

Acknowledgements

Thank you to Jonathan Kung, our NETL project manager.

I.18 Micromobility Screening for City Opportunities Online Tool (University of Washington)

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Start Date: October 1, 2019	End Date: December 31, 2022	
Project Funding (Initial): $145,218	DOE share: $129,218	Non-DOE share: $16.000
Project Funding (FY20-FY21): $189,670	DOE share: $170,670	Non-DOE share: $19,000
Total Expected Project Funding: $334,888	DOE share: $299,888	Non-DOE share: $35,000

Project Introduction

Micromobility services (emerging personal mobility modes based on very small vehicles, typified by bike sharing and scooter sharing) have been booming over the past several years, as companies have flooded American cities with scooters and bikes. The industry has now entered a phase of rationalization in search of profitability, even as many cities are scrambling to manage the impacts of these vehicles and ensure that their benefits are available to all. Industry, local governments, researchers, and DOE need a tool that can screen cities and neighborhoods to identify areas where there is a high opportunity for micromobility to gain market share, improve accessibility, and/or improve mobility energy productivity relative to incumbent modes. This will allow micromobility resources to be deployed in numbers and locations that deliver benefits to residents and cities while maintaining high utilization of industry assets.

Objectives

The objective of this project is to develop a new analytical tool that uses real-world data to estimate energy use and associated impacts of micromobility services. The micromobility Screening for City Opportunities Online Tool (SCOOT) will be an extensible framework for assessing census tract-level demand for, and benefits from, micromobility services in all metropolitan statistical areas (MSAs) across the United States. SCOOT will integrate new and previously collected data to evaluate and display the market potential, accessibility, energy productivity, and emissions savings associated with micromobility services. The framework will be readily adaptable to alternative models of trip generation and mode choice, different levels of geographic aggregation, and user-specified assumptions about the cost and availability of micromobility vehicles. The modeling system will be implemented in an online tool accessible to the public, and the underlying code will be open source in order to facilitate further development by DOE, national labs, or the private sector.

Approach

The tasks to develop SCOOT are spread over two budget periods. Budget period 1 (October 2020 – December 2021) has focused on gathering necessary background information, assembling data, and building the constituent sub-models. Activities in budget period 2 (January – December 2022) will focus on integrating these sub-models into the SCOOT framework, validating its outputs, and implementing it as an online tool.

More specifically, work over the past 12 months has included:

- Review of prior literature related to trip generation, mode choice, mode substitution, and environmental impacts related to micromobility services.

- Inventory of publicly available micromobility ridership data from each of the top 20 American cities by population, and from a sample of 20 more out of the next 80 largest American cities.
- Design of a stated preference / revealed preference questionnaire that links micromobility use with price, access distance, socio-demographics, local land use, and availability of compatible infrastructure (e.g., bike lanes).
- Estimation of statistical models of the number of daily trips each individual generates and the distribution of trip lengths.
- Generation of a synthetic population to represent travelers across census tracts in all American MSAs.

Efforts in the remainder of budget period 1 will focus on completing the necessary components for SCOOT. Specifically, this will include administering the stated preference / revealed preference questionnaire via an online survey and estimating a model of mode choices including micromobility options, conditional on attributes of the mode, individual, and environment. Moving into budget period 2, work will shift to integrating the constituent models into the SCOOT framework. The framework will be applied to the synthetic population to predict the utility of each mode and the number of micromobility trips based on individual attributes, local land use, and infrastructure data. Predicted trip counts will be validated against publicly available data. Calculations of accessibility, mobility energy productivity, and GHG emissions will be conducted, each with and without micromobility available. Finally, the SCOOT framework will be implemented into an interactive, web-based tool, tested, and refined.

Results

The review of the literature identified several critical gaps in knowledge that represent priorities for investigation. First, dockless micromobility systems need more attention from researchers. Rich ridership data enabled extensive studies of station-based micromobility systems, but limited data means that less is known regarding the travel behavior of dockless system users, especially in American cities. Future research could complement the limited data from service providers and application programming interfaces with survey data for analyzing dockless systems [1]. Efforts are also needed to encourage collaboration with service providers for better data sharing strategies that enable more research to help micromobility thrive.

Second, relationships between individual latent attitudes and the intention to use micromobility have been only lightly investigated. In particular, quantitatively examining the magnitudes of effects of psychometric factors and the social environment on micromobility mode choices and exploring how the COVID-19 pandemic may affect travelers' risk perceptions and attitudes towards the use of micromobility, are possible research directions as well [2],[3].

Finally, there are considerable gaps in understanding the impacts of micromobility services. Specifically, the performance of micromobility services is largely based on the local context; thus, disaggregate analysis using individual-level inputs is necessary [4]. Also, a comprehensive mode choice model and travel demand model should be developed to test and forecast the impact of micromobility on mode shift and transit integration potential under different scenarios. Moreover, most research only focuses on city-level case studies. A flexible modeling framework that could be applied and inferred at multiple geographic scales would provide valuable insights into the development and expansion of micromobility services.

The inventory of ridership data for micromobility services undertaken as part of this study identified publicly available data in 8 of the top 20 largest American cities by population. An inventory covering a sample of 20 out of the next 80 largest cities found publicly available data in just 3 cities. Overall, across the 40 cities inventoried, 31 had dockless scooters, 26 had docked bikeshare, and 24 had dockless bike share. Of these, five had data available for scooters, eight for docked bikeshare, and six for dockless bikeshare.

Models of the number of daily trips each individual generates, and the distribution of trip lengths were estimated using data from the 2017 NHTS. The NHTS contains a total of 923,572 records of trips made by 219,194 individuals from 117,222 American households. Since trip counts are small, nonnegative integers, with unequal mean and variance, a negative binomial count model was used to model the number of trips per day made by travelers. Key predictor variables include individual (e.g., race, gender, educational attainment), household (e.g., size, income), and residential location (e.g., density) characteristics. Model results are summarized in Table

I.18.1. For the trip length model (Table I.18.2), similar variables plus trip purposes were used to estimate the logged trip miles, leaving out trips that were recorded as zero miles.

Table I.18.1 Negative Binomial Trip Count Model Where the Dependent Variable is the Number of Trips Made by Each Individual During the Travel Day Recorded in the 2017 NHTS

	Estimate	Standard Error	P-value	Significance
(Intercept)	1.189	0.011	<0.001	***
Age	0.001	0.000	<0.001	***
Education (Reference: less than high				
High school	0.060	0.007	<0.001	***
Some college	0.125	0.007	<0.001	***
Bachelor	0.189	0.007	<0.001	***
Graduate	0.209	0.007	<0.001	***
Female	0.041	0.003	<0.001	***
Household Size	-0.002	0.001	0.173	
Household income (Reference: <$10,000)				
$10,000-$14,999	0.020	0.010	0.041	**
$15,000-$24,999	0.028	0.008	0.001	***
$25,000-$34,999	0.029	0.008	<0.001	***
$35,000-$49,999	0.039	0.008	<0.001	***
$50,000-$74,999	0.034	0.008	<0.001	***
$75,000-$99,999	0.026	0.008	0.001	***
$100,000-$124,999	0.029	0.008	<0.001	***
$125,000-$149,999	0.028	0.009	0.001	***
$150,000-$199,999	0.029	0.009	0.001	***
$200,000 or more	0.052	0.009	<0.001	***
Household tract density (people/mile2)				
100-499	0.005	0.005	0.287	
500-999	0.019	0.005	<0.001	***
1,000-1,999	0.031	0.005	<0.001	***
2,000-3,999	0.032	0.005	<0.001	***
4,000-9,999	0.041	0.004	<0.001	***
10,000-24,999	0.031	0.007	<0.001	***
25,000-99,999	0.034	0.011	0.003	***
Nonworker	0.015	0.003	<0.001	***
Race (Reference: White)				
Black	-0.023	0.005	<0.001	***
Asian	-0.112	0.006	<0.001	***
American Indian or Alaska Native	0.030	0.016	0.071	*
Native Hawaiian or other Pacific Islander	-0.102	0.027	<0.001	***
Multiple	0.020	0.008	0.012	**

Other	-0.066	0.009	<0.001	***

Table I.18.2 Ordinary Least Squares Trip Length Model Results Where the Dependent Variable is the Logged Length of Each Trip Recorded in 2017 NHTS

	Estimate	Standard Error	P-value	Significance
(Intercept)	0.757	0.014	<0.001	***
Age	0.000	0.000	0.653	
Education (Reference: less than high				
High school	0.064	0.009	<0.001	***
Some college	0.043	0.008	<0.001	***
Bachelor	-0.037	0.009	<0.001	***
Graduate	-0.097	0.009	<0.001	***
Female	-0.085	0.003	<0.001	***
HHSIZE	0.036	0.001	<0.001	***
Household income (Reference: <$10,000)				
$10,000-$14,999	0.069	0.012	<0.001	***
$15,000-$24,999	0.180	0.011	<0.001	***
$25,000-$34,999	0.258	0.011	<0.001	***
$35,000-$49,999	0.348	0.010	<0.001	***
$50,000-$74,999	0.406	0.010	<0.001	***
$75,000-$99,999	0.466	0.010	<0.001	***
$100,000-$124,999	0.484	0.010	<0.001	***
$125,000-$149,999	0.512	0.011	<0.001	***
$150,000-$199,999	0.493	0.011	<0.001	***
$200,000 or more	0.473	0.011	<0.001	***
Nonworker	-0.057	0.004	<0.001	***
Purpose (Reference: Home-based other)				
Home-based Shopping	0.031	0.005	<0.001	***
Home-based Social/Recreational	-0.055	0.006	<0.001	***
Home-based Work	0.727	0.006	<0.001	***
Non-home based	-0.114	0.005	<0.001	***
(Intercept)	0.757	0.014	<0.001	***

A preliminary synthetic population has been constructed to represent a sample of the U.S. population. This sample includes all individuals residing in MSAs. This was accomplished through population synthesis, a process by which surveyed microdata samples are reweighted to represent a set of known marginal counts for different geographic regions. In this case, microdata from the Census Bureau's Public Use Microdata Samples (PUMS) were reweighted according to marginal counts provided by the American Community Survey (ACS), using the PopulationSim population synthesizer [5]. Generation of this preliminary synthetic population took approximately 20 minutes per MSA, or 104 hours to complete all MSAs on a standard desktop computer with multi-processing. The distributions of each control variable in the unweighted and synthetic PUMS data are compared in Figure I.18.1.

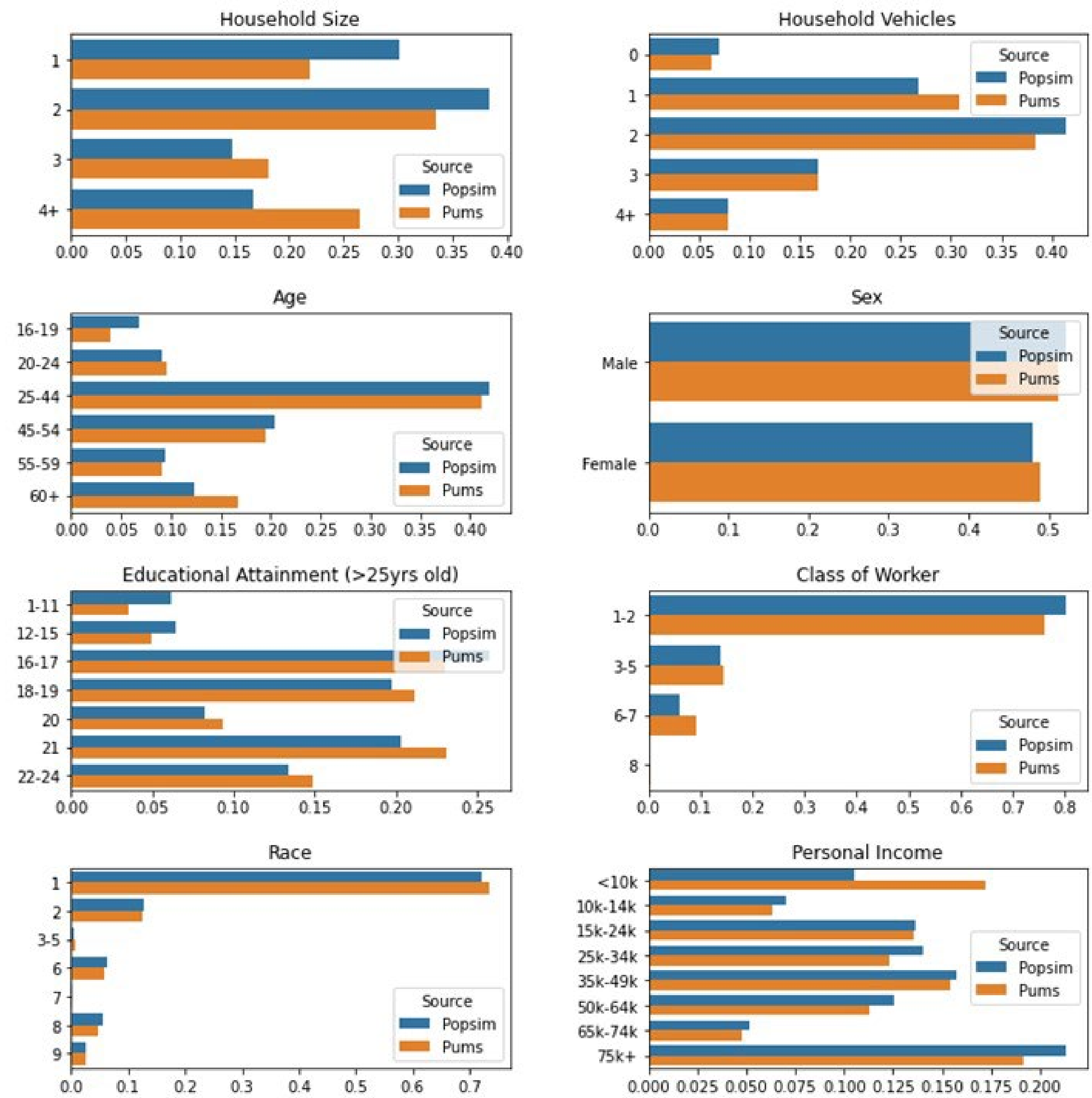

Figure I.18.1 Distributions of control variables in unweighted (PUMS) and synthetic (PopulationSim) datasets. Source: University of Washington

Conclusions

The key accomplishments completed so far in this project include the design of an online survey questionnaire, assessment of the relationship between key predictor variables and trip-making decisions, and an inventory of publicly available micromobility ridership data from cities across the United States. Alongside several other tasks completed during this period, the project activities have provided the necessary building blocks for achieving the key remaining objectives as the project continues into the second budget period: (i) integrating the SCOOT framework, which will evaluate and display the market potential, accessibility, energy productivity, and emissions savings associated with micromobility services, and (ii) implementing SCOOT as an open source, web-based tool.

Key Publications

Zou, T., Steinberg, W., MacKenzie, D. What Are the Determinants and Impacts of Shared Micromobility? A Review of Recent Literature. *Transportation Research Board Paper No. 22-03270*. Transportation Research Board 101st Annual Meeting. January 2022.

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2. Zheyan Chen, Dea van Lierop, and Dick Ettema. "Dockless Bike Sharing Systems What Are the Implications," *Transport Reviews* 40, no. 3 (January 2020): 333–53.

3. Kailai Wang, Xiaodong Qian, Giovanni Circella, Yongsung Lee, Jai Malik, and Dillon Taylor Fitch, "What Mobility Modes Do Shared E-Scooters Displace? A Review of Recent Research Findings," Paper Presented at the *100th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2021.* https://annualmeeting.mytrb.org/OnlineProgram/Details/15657

4. Yujie Guo, Zhiwei Chen, Amy Stuart, Xiaopeng Li, and Yu Zhang, "A Systematic Overview of Transportation Equity in Terms of Accessibility, Traffic Emissions, and Safety Outcomes: From Conventional to Emerging Technologies," *Transportation Research Interdisciplinary Perspectives* 4 (March 2020): 100091. https://doi.org/10.1016/j.trip.2020.100091

5. Binny Matthew Paul, Jeff Doyle, Ben Stabler, Joel Freedman, and Alex Bettinardi, "Multi-level population synthesis using entropy maximization-based simultaneous list balancing," Paper Presented at the *97th Annual Meeting of the Transportation Research Board, Washington, D.C., January 2018.*

Acknowledgements

This work represents the efforts of research assistants Tianqi Zou, Zack Aemmer, and Will Steinberg. The team thanks Adrienne Riggi and Raphael Isaac for their support of this project and valuable feedback throughout.

I.19 Development of Heavy-Duty Electric Vehicle Integration and Implementation (HEVII) Tool (University of Minnesota)

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Start Date: October 1, 2020	End Date: December 31, 2022	
Project Funding (Initial): $221,969	DOE share: $200,872	Non-DOE share: $21,097
Project Funding (FY20-FY21): $221,480	DOE share: $198,577	Non-DOE share: $22,903
Total Expected Project Funding: $443,449	DOE share: $399,449	Non-DOE share: $44,000

Project Introduction

Increased electrification is a clear trend in regional trucking, with multiple vehicle manufacturers bringing to market commercially available battery electric and hydrogen fuel cell Class 6–8 trucks. On the fleet side, at least 70% of major truck fleet operators reported exploring purchase and implementation of electric vehicles for their operations as of 2018. Recently, multiple high-profile companies including PepsiCo, Walmart, Amazon, and the United Parcel Service have publicly committed to the purchase of electric delivery vehicles. Despite these commitments, companies have yet to implement these vehicles at scale due to a combination of range anxiety, limited charging infrastructure availability, and sparse data from in-use operation. Further, electric vehicle implementation has occurred disproportionately among larger fleets with more resources. With successful heavy-duty EV implementation being highly dependent on vehicle duty cycle, including vehicle mass and road grade as well as external factors like climate and traffic, any electrification recommendation must be tailored to the individual fleet and vehicle. To address these concerns and to enable large scale electric vehicle adoption this project is developing a publicly available Heavy-Duty Electric Vehicle Integration and Implementation (HEVII) tool to both assess heavy duty electric vehicle suitability and to identify necessary infrastructure improvements, both public and private.

Objectives

The main objectives of this project are to: (1) Conduct a vehicle duty cycle analysis representative of two regional Class 6–8 commercial vehicle fleets; (2) Develop a model using a novel mass prediction algorithm that uses fleet trajectory data to estimate EV range and applicability; (3) Develop an integrated charger location estimation tool to determine infrastructure requirement for fleets and municipal corridors; and (4) Validate the developed tool using data from in-use EV trucks operating in two metropolitan regions.

Approach

The developed tool will utilize existing telematics information collected from conventionally powered, heavy-duty vehicles in regional delivery fleets combined with a vehicle model and optimization code to predict battery size and on-route charging locations required to complete the same desired work. The project is proceeding in four stages: (1) Data collection and simplified data analysis; (2) In-depth analysis and mass prediction; (3) Analysis of vehicle fleets and on-route charging; and(4) in-service validation and pertinence to broader applications.

The HEVII tool itself leverages multi-fidelity in-use vehicle data to provide owners with customized electrification requirements including battery size, charge rate, and infrastructure placement. This tool is advanced compared to other available methods because it uses a physics-based vehicle model with an autotuning feature, predicts vehicle mass to improve electric vehicle energy use estimation accuracy, simultaneously identifies component sizing and charging infrastructure requirements, functions with different data types including sparsely collected telematics data, and is open source and available to the public.

Results

The project team has completed the initial task to collect data from selected vehicles in the PepsiCo fleet and to perform a simplified analysis on the data. The team also worked to refine two methods for determining mass from vehicle data sampled at sparse time resolution, a challenge for conventional techniques. A process flow diagram for the HEVII tool is given in Figure I.19.1. The tool takes telematics data collected from fleets of conventional trucks and uses them to determine vehicle mass and run analyses to determine electrification potential and charging infrastructure placement.

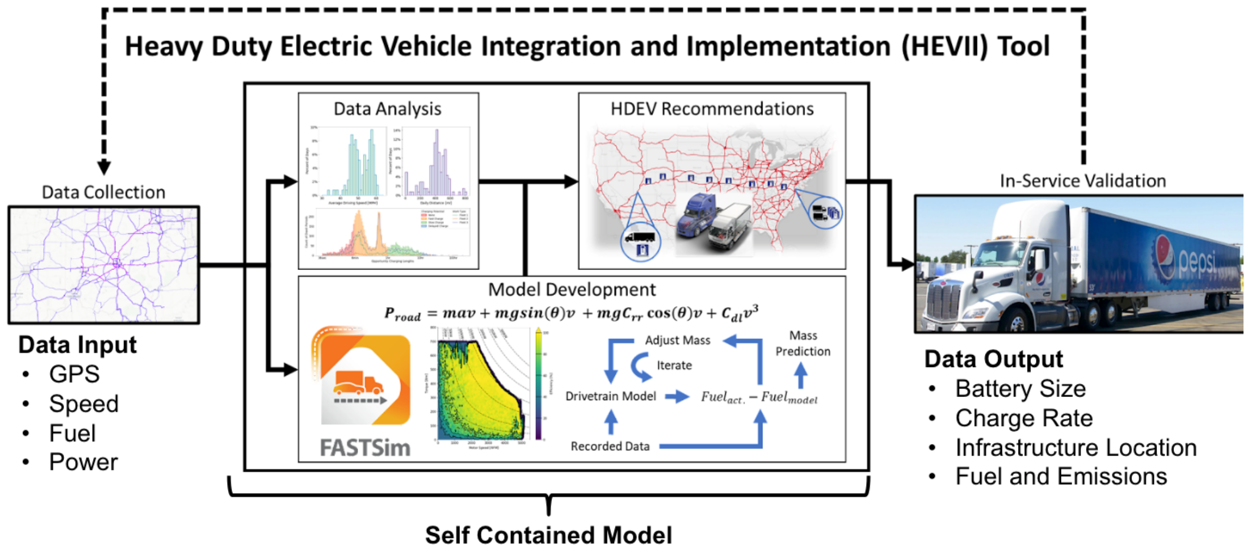

Figure I.19.1 Process flow diagram of the overall HEVII tool to be developed in the project. Source: University of Minnesota

Data collected from the PepsiCo fleet were added to test and production databases on separate PostgreSQL 10.x servers accessible by the project team. A final schema continues to evolve as the team identifies how best to handle and use the data in the development of the HEVII tool. Vehicle measurements, location, speed, and trip records are populated in the database. Unfilled and linearly interpolated sparse time-series data, filled to 1 Hz, are available in the database for PepsiCo vehicles and for a small number of NREL vehicles, using data extracted from Geotab, Inc. (Geotab) loggers. As planned, 24 baseline vehicles were selected from each of two locations for the development of the tool. The aggregated Global Positioning System (GPS) tracks of these vehicles from two months of driving are shown in Figure I.19.2.

Mass detection is a critical factor in calculating electric vehicle energy use. Class 6–8 vehicles can have a large mass variation on the road depending on their payload. Figure I.19.3 shows how assuming a fixed mass for a truck can lead to large deviations in predicted fuel used over the course of a trip. Here NREL's FASTSim tool was used to model a truck with (i) changing mass and (ii) fixed mass, with results compared to actual vehicle data. It is clear from the figure that if a fixed mass is used, the energy use deviates significantly over the course of the trip. In the given example, the model with fixed mass predicts a much higher energy use than the actual data, most likely due to the truck being unloaded at some point during its journey. However, if mass is allowed to change during the trip, the energy use can be predicted with better accuracy.

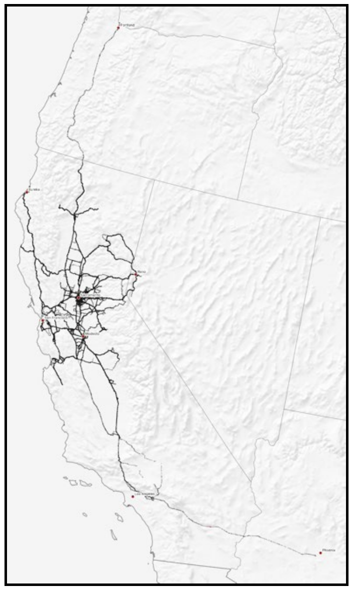

Figure I.19.2 Aggregated GPS traces of all 24 baseline PepsiCo trucks used in the study for a two-month period. Source: University of Minnesota

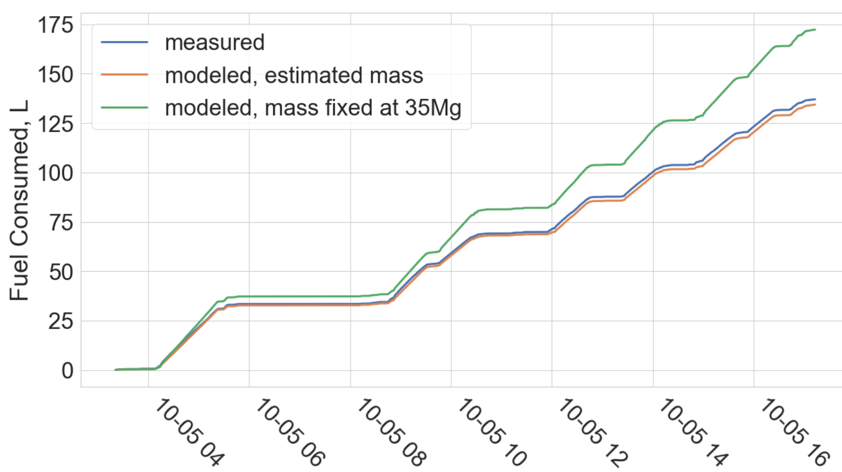

Figure I.19.3 Cumulative fuel used by a truck over the course of a trip using the measured mass, calculated mass, and fixed mass. Source: University of Minnesota

Mass is not always calculated and reported to telematics devices in vehicles and is rarely measured by a scale before a truck and trailer leaves a warehouse. NREL researchers have reported that mass can be calculated using the road load equation and known fuel use over time when telematics data are taking on a regular once per second (1 Hz) basis [1]. However, the cost of 1 Hz data is high for all vehicles in a fleet over the course of a year, with loggers costing $700 to $5,000 and cellular plans costing $30 to $60 per month per vehicle depending on usage. Geotab records more sparse data using curve sampling [2], which cuts down on data costs by reporting a value only once it changes by a predetermined level. NREL has developed a new mass algorithm for this project that uses only 1 Hz data collected in short 30 second windows triggered by a stop event. The results from the original NREL algorithm from a full set of 1 Hz data are compared to those taken by the new algorithm and to direct onboard observational sensor data. Figure I.19.4 shows that during periods where the mass is constant, the short window mass results are sometimes closer to the sensor data than the results taken from the full dataset. In subsequent analyses, it was found that the new 30-second algorithm results in similar accuracy to using the full data set, but with significantly less data transmission cost. In the second year of the HEVII project Geotab will implement periodic 1 Hz data collection after stop events in its loggers on the 24 selected vehicles in the project.

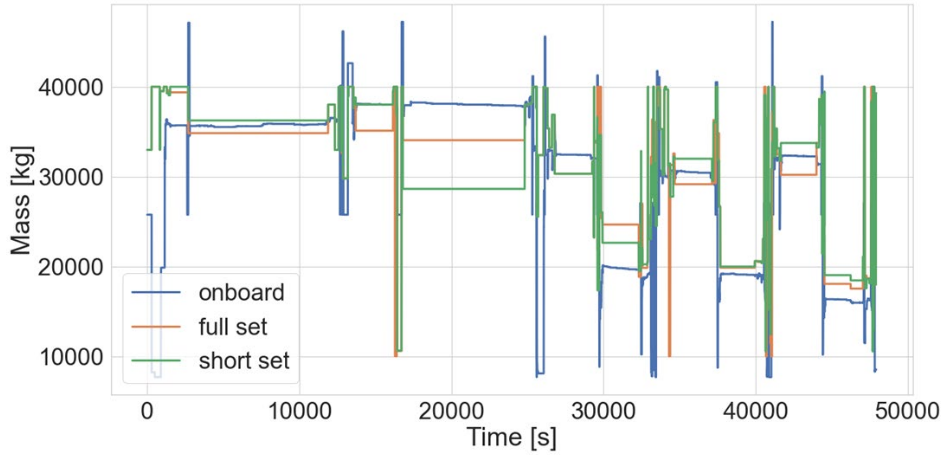

Figure I.19.4 Mass for a Class 8 truck from an onboard sensor compared to the NREL mass calculation using 1 Hz data (full set) and data collected in 30 second windows (short set). Source: University of Minnesota

A second mass detection algorithm, one that uses ML approach, has also been developed as part of the HEVII project. Gaussian belief propagation (GBP) is a relatively new marginal inference algorithm that uses an arbitrary factor graph model to make probabilistic estimates according to the marginal distributions in historical data [3]. Once GBP is applied to fit a predictive line to the available mass data, the k-nearest neighbors algorithm can be used to predict the mass of new points based upon the similarity of the new point's input vector to those of training points [4]. The proposed input vector for this study includes 9 parameters collected from PepsiCo trucks: engine speed, reference torque, engine load, velocity, acceleration, change in fuel level, longitude, latitude, and time of day. This approach may work effectively on curve sampled data collected by Geotab directly and can be trained using a smaller amount of data than other ML techniques such as neural networks or reinforcement learning models. The GBP method will be compared to NREL's physics-based approach in the second year of the HEVII project.

The HEVII tool for evaluating EV transition potential for truck fleets is also under development. As part of this effort, NREL has developed preliminary methods that utilize vehicle trajectories from multiple vehicles to analyze and determine electrification potential. To predict fleet energy use, the trucks are simulated using the historical drive cycle data and a developed electric truck model. In the initial analysis, trucks were allowed to charge at past stops in the historical driving data. The trucks were only allowed to charge during the original stop duration in the given location. By simulating the drive cycles and incorporating on-route charging, the team was able to estimate the fleet energy usage over time. This method assumes that the routes or at least the drive cycles of the trucks in a fleet would remain consistent regardless of the truck powertrain.

Preliminary research has also been conducted to develop an approach for fleet electric truck charger placement location. As this is the first phase for the HEVII tool, the model has been simplified to determine optimality of the approach. Before the optimization model can be created, the team first determined how to represent the geospatial data from the database to visually analyze the routes and patterns. One method would be to plot a series of GPS coordinates, then cluster them based on their density. Although this method is valid, it may be difficult to accurately classify nearby points, by trajectory, within an area. It is easier to develop a grid system where the points are constrained within a fixed shape and to analyze the behavior of the points within that region.

The charger station location problem developed for the HEVII tool incorporates the Uber H3 open-source code to formulate a grid framework to view geospatial data and determine insights from the vehicle data. The H3 source code is a geospatial tool that assigns variably sized hexagons (scale grid) to large geographical datasets by changing the resolution [5]. The reason hexagons were chosen over rectangles, triangles, etc. is because only one distance is calculated between the center of a given hexagon and its neighbors, something that is computationally efficient and simplifies the analysis. The approach locally defines zones by using a hexagonal shape to draw over a neighborhood, city, etc. The H3 code has several functions such as the ability to index k-nearest neighbors, combine with map application programming interface, change the resolution, etc. As shown in Figure I.19.5, as the resolution increases, the smaller the hexagons are within the chosen coordinates, city, etc. This source code can be utilized with a mapping API such as Google Maps, which allows a visual representation of and geographical information for each hexagon. This code includes implementing reverse geocoding that can be used to convert a given coordinate to a physical text address (both for look-up purposes and for ease of consumer use).

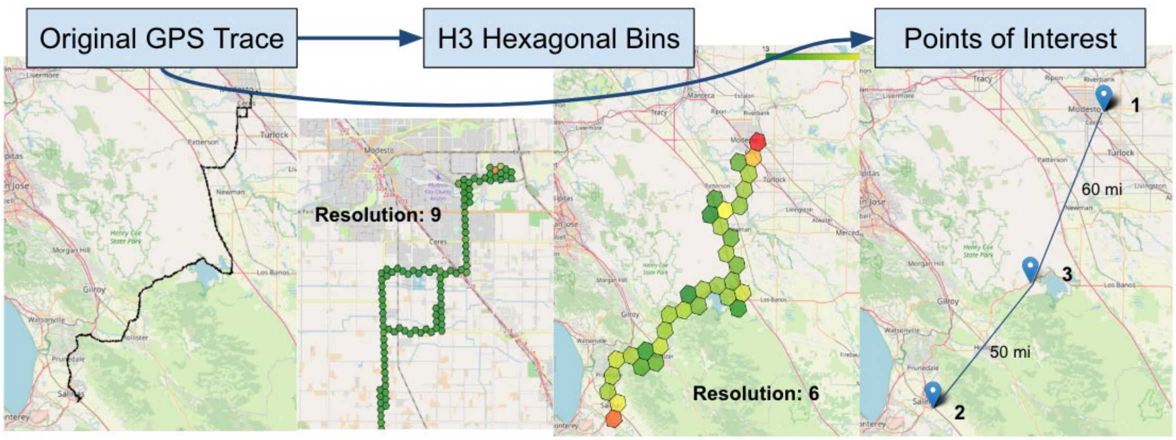

Figure I.19.5 Example of using the GPS data from a PepsiCo truck to determine optimal charging location based on travel frequency at two different H3 hexagonal resolutions in combination with ranked points of interest. Source: University of Minnesota

By implementing the H3 source code, the HEVII database is used to incorporate geofenced points of interest and vehicle driving patterns (i.e., stop duration) to develop a visual representation of the geospatial data and to create an optimization model with some objective function that can solve the charger station location problem . With this source code, the best charger locations can be determined, depending on the specific levels of activity (i.e., demand), such that wait times, costs, etc. are reduced. For simplicity, the initial HEVII tool prototype will determine charger station locations by utilizing common stop locations from the vehicle data. Charge delays will be reduced using multiple vehicle trajectories from a fleet to help optimize the number of chargers required at prioritized stations. The research team also plans to integrate a cost model (i.e., electricity costs, charger cost, etc.) that will account for regional differences and emission predictions into the optimization algorithm.

Conclusions

In conclusion, the open source HEVII tool is under development and is expected to be available as a prototype at the end of this two-year project. The project teams at University of Minnesota and NREL have developed a framework for the eventual tool, established two methods of mass estimation from low resolution telematics data, and determined a method for solving the charger station location problem. Future project work will aim to further refine the methods developed in the first year of the project and to create an open-source prototype HEVII tool for evaluation by fleets and other researchers.

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Acknowledgements

The project team would like to acknowledge project partners, Hani Hawari of Geotab and Emily Conway and Brenden Wiggins from PepsiCo, for their contribution to the project.

I.20 Integrated Modeling and Technoeconomic Assessment of Electric Vehicle Community Charging Hubs (University of Illinois at Urbana-Champaign)

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Start Date: October 1, 2020	End Date: December 31, 2023	
Project Funding (Initial): $242,948	DOE share: $219,008	Non-DOE share: $23,940
Project Funding (FY20-FY21): $145,952	DOE share: $130,992	Non-DOE share: $14,960
Total Expected Project Funding: $388,900	DOE share: $350,000	Non-DOE share: $38,900

Project Introduction

Community charging hubs are expected to become essential for residents of multi-unit dwellings (MUDs) during the mass market transition to EVs due to a sparse network of public charging stations in proximity to such residences.

The existing literature on EV charger deployment focuses on modeling intra- and inter-regional charging station siting [1],[2], often assuming universal home charging availability [3],[4]. However, less than 50% of household vehicles have access to dedicated parking in residences where charging installation and use could be undertaken [5]. Limited access to home charging opportunities could hinder the adoption [6] and use of EVs [7] and slow down the decarbonization of the United States light-duty transportation sector [8]. The existing literature fails to propose novel concepts to solve charging challenges that MUD residents may face when operating an EV, challenges that could serve as impediments to mass electrification and market penetration. Past research has primarily focused on policymaking levers for installation of chargers in MUDs (e.g., [9]) or assessed the financial viability of charging station business models (e.g., [10]). A comprehensive feasibility evaluation of the novel concept of community charging hubs for MUDs with EV charging session scheduling algorithms, including total energy use estimation in this setting, is lacking. This project seeks to significantly expand the existing literature in this domain with new computational methods while proposing tangible solutions to address the EV adoption and operation bottleneck that has begun to develop and is otherwise likely to worsen as a result of the obstacles to charging currently faced by MUD residents.

Objectives

A lack of home charging access could hinder the adoption and operation of electric vehicles by MUD residents [5]. Community charging hubs will enable (a) residents of MUDs to recharge their EVs using smart charging scheduling and (b) efficient sharing of charging infrastructure at MUDs. This study classifies the daily travel patterns of MUD residents and simulates their electric vehicle operations, leveraging open-access survey data from the NHTS [11] and socio-demographic data from the ACS [12] and the American Housing Survey (AHS) [13].

Due to a lack of EV home charging data, spatiotemporal datasets of travel patterns of MUD residents are analyzed and classified. The objective is to capture time-of-day variations in automobile travel for MUD residents and create a representative repository of their travel profiles. After extracting MUD residents' travel patterns with conventional vehicles, a simulation of expected EV daily operation is performed, tracking both the SOC and the dwell times in between trips. Granular time-of-day travel clusters of MUD residents are used to determine optimal charging choices (i.e., between home, workplace, and public options) that minimize costs under several scenarios. The outcomes of the optimal charging analysis provide insights into MUD charger deployment needs and estimated energy use.

Approach

In order to assess travel profiles and the characteristics of MUD residents, the latest data available from the 2017 NHTS [11] and the 2019 AHS [13] have been analyzed. NHTS served as the primary database used for the daily travel analysis, selected for this role as it is a source regularly leveraged to infer electric vehicle daily mileage and charging needs in the U.S. (e.g., [14],[15]). However, this data source lacks information on vehicle owners' housing type (i.e., multi-unit dwelling, single family house), which can impact assumptions made regarding home charging availability and access [5].

To match the NHTS household-level travel data with the MUDs share from AHS, a statistical model that predicts the share of MUDs has been fitted, using a function of variables that are included in both datasets. Variables included in both AHS and NHTS span socio-demographic characteristics, such as income and location. The existing literature demonstrates that income and location characteristics are significant covariates in predicting the housing unit type of a household [16],[17]. The ordinary least squares method was used, with the resulting linear regression model leveraging income and census division variables to predict the share of MUD residents. Average household income is negatively associated with MUD share in a region, while each location's effect is also captured in the model. The linear regression model, which is fitted with AHS data, is then applied using NHTS observations to estimate the share of MUDs for each observation. Finally, MUD residents' travel data are synthesized by assigning a binary indicator to each household in the NHTS trip database based on the location and income level. The robustness of 100 simulation results has been confirmed by examining the time-of-day VMT distribution.

After highlighting trends in time-of-day variation of the automobile travel patterns of MUD residents, the patterns are clustered in order to uncover distinctive driver behaviors. To create clusters of time-of-day travel patterns, aside from the variables of income, census division, and trip travel time, new covariates are generated including dwell time at home, dwell time at work, and dwell time at a public location, as well as VMT and vehicle location per time of day. Vehicle location is denoted as a categorical variable of "home", "workplace", "public", and "driving". A hierarchical agglomerative classification algorithm was implemented to determine travel behavior classes, after the normalization of all variables.

In order to estimate the electric vehicle charging infrastructure needs of MUD residents, under assumptions of universal EV adoption and use, an optimization problem was formulated to determine optimal use at hypothesized MUD charging hubs. Such charging stations need to be deployed accounting for drivers' decisions and charging availability across the different locations of trip stops during the day (e.g., MUDs, workplaces, public destinations). Therefore, the optimization problem was developed in order to determine optimal charging requirements for and charging energy use of MUD residents, and the optimal deployment of charging stations at MUDs. The problem's objective function is set to minimize the driver's charging cost, accounting for charging availability, and determine charging decisions of EVs and their owners. Model constraints are as follows:

- Capture the charging electricity cost per unit of time for charging an MUD household's vehicle;

- Present the state transition functions that update the mileage range of a vehicle at a trip's stop;
- Ensure that the mileage range of a vehicle is not less than the comfortable driving range;
- Enforce that mileage range is equal to or greater than the comfortable mileage during intermediate trips;
- Ensure that the charged range miles do not exceed the difference of the full range and current range;
- Ensure that charging time does not exceed the dwell time;
- Demonstrate that if there is charging availability at the MUD location for a vehicle then the charging time can be nonnegative; and
- Ensure that charging station availability variables are binary and charging time variables are nonnegative.

Results

Shares of each residence type are available through AHS data: 71% of U.S. residential structures have one housing unit while 24% are multi-unit dwellings. (An additional 5% fit into neither of the above categories.) Thus, single-family housing is the most common housing type in the US. The greatest share of MUDs is found in the Middle Atlantic region (34.1%) and the lowest in the East South Central region (15.4%), as can be seen from Figure I.20.1. MUD shares are higher in lower income groups, while the lowest MUD shares are concentrated in the highest income groups. VMT among predicted MUD residents are lower than those of single-family unit residents. The median share of time spent at home over 24 hours of a day (as a percentage) is not significantly different between housing types, and for all census divisions and housing types falls within the 60%-70% range. More than 80% of vehicles are parked at home by 10:00 p.m., remaining that way until 7:00 a.m. Approximately 20% of vehicles are parked at work by 9:00 a.m. Vehicles spend between 4 and 10 hours parked at working premises.

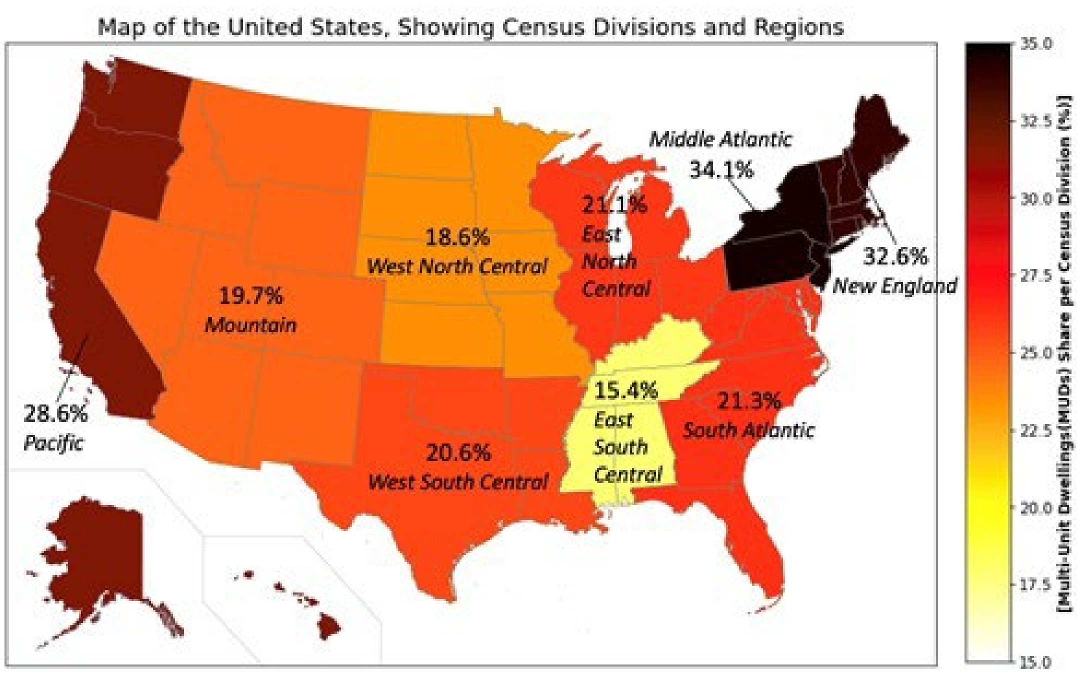
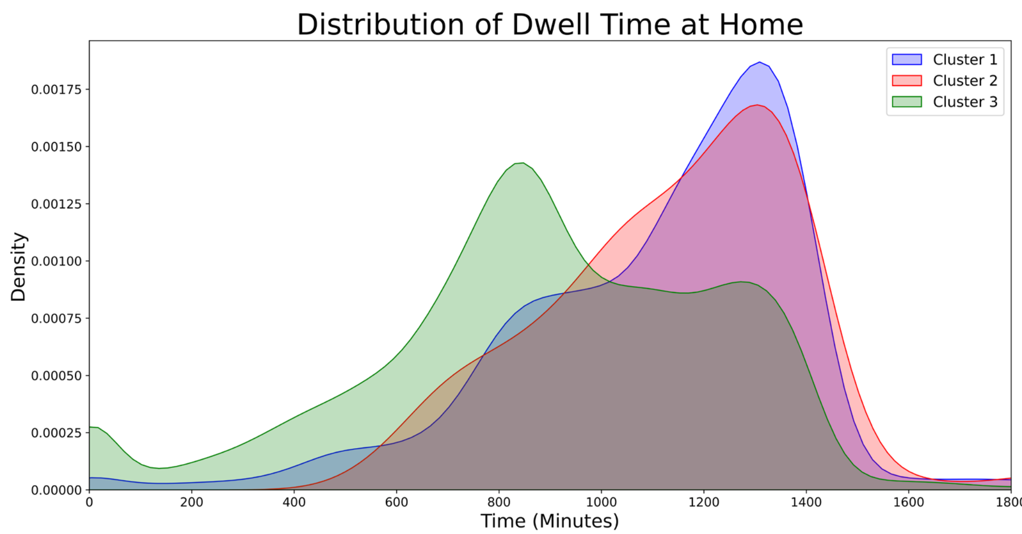
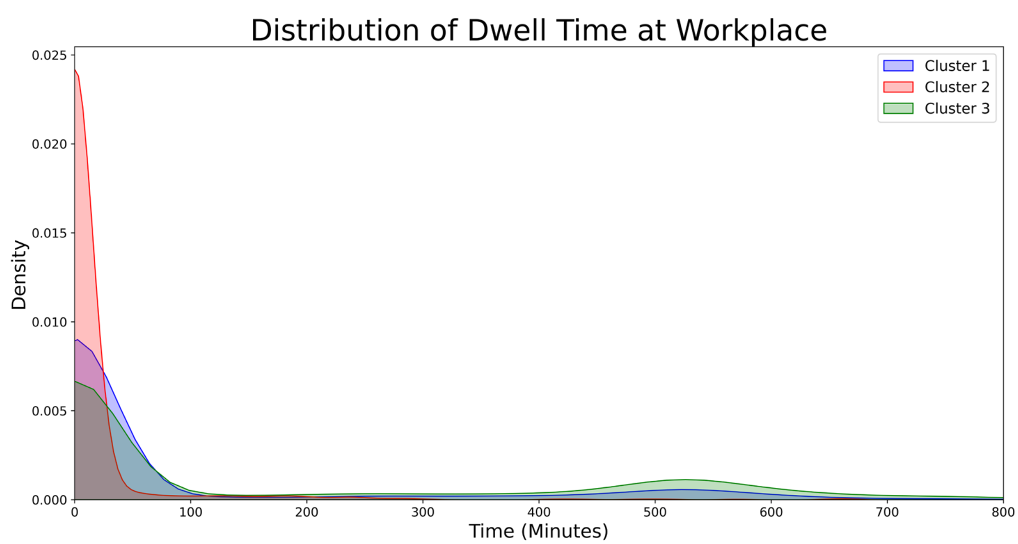


Figure I.20.1 MUDs share per census division. Source: University of Illinois at Urbana-Champaign

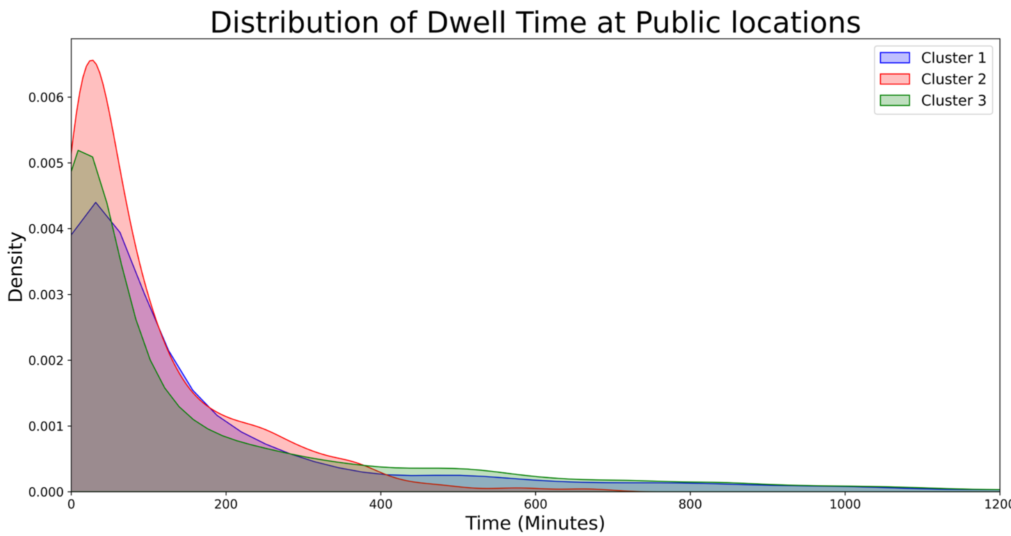
Three clusters best describe the MUD residents' travel patterns, as seen in Figure I.20.2. Cluster 1 and cluster 2 have similar average dwell time at home. However, these two clusters differ in terms of average dwell time at work and public locations. Cluster 2 spends their day primarily at home, when cluster 1, being less outgoing than cluster 3 drivers, spends their day primarily between home and work. The greatest share of daily travel for MUD residents belongs to cluster 3, for which the average dwell time at home is shorter, while the dwell times at workplace or public location are greater than for the rest of the drivers' clusters.



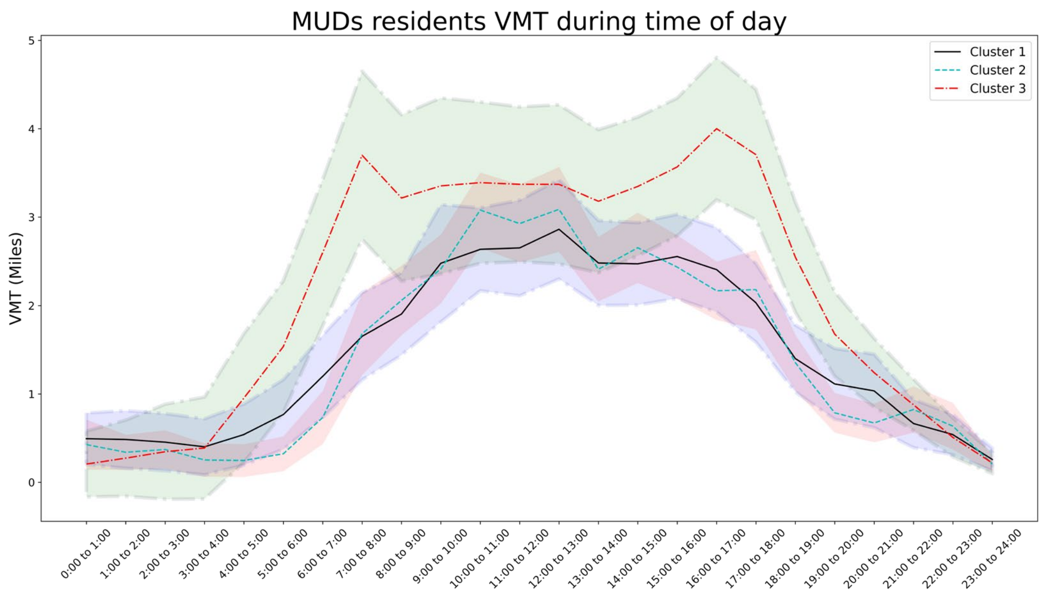
(a)



(b)



(c)



(d)

Figure I.20.2 MUDs share per census division. (a) Distribution of dwell time at home, (b) distribution of dwell time at the workplace, (c) distribution of dwell time at public locations, and (d) MUD residents VMT during the time of day. Source: University of Illinois at Urbana-Champaign

The expected deployment share of MUD charging stations is depicted in Figure I.20.3. Two scenarios are examined: EVs maintain 20 miles SOC as a comfortable range all day, or EV drivers ensure recharging that meets or exceeds the boundary of 80 miles of range at the end of the day. For a portion of residents, accommodating their trips with electric vehicles is infeasible, due to the strict SOC boundaries set, or due to the residents' travel patterns. Accounting for the remaining residents, modeling results are reported, presenting the share of MUD residents who require MUD charging station deployment.

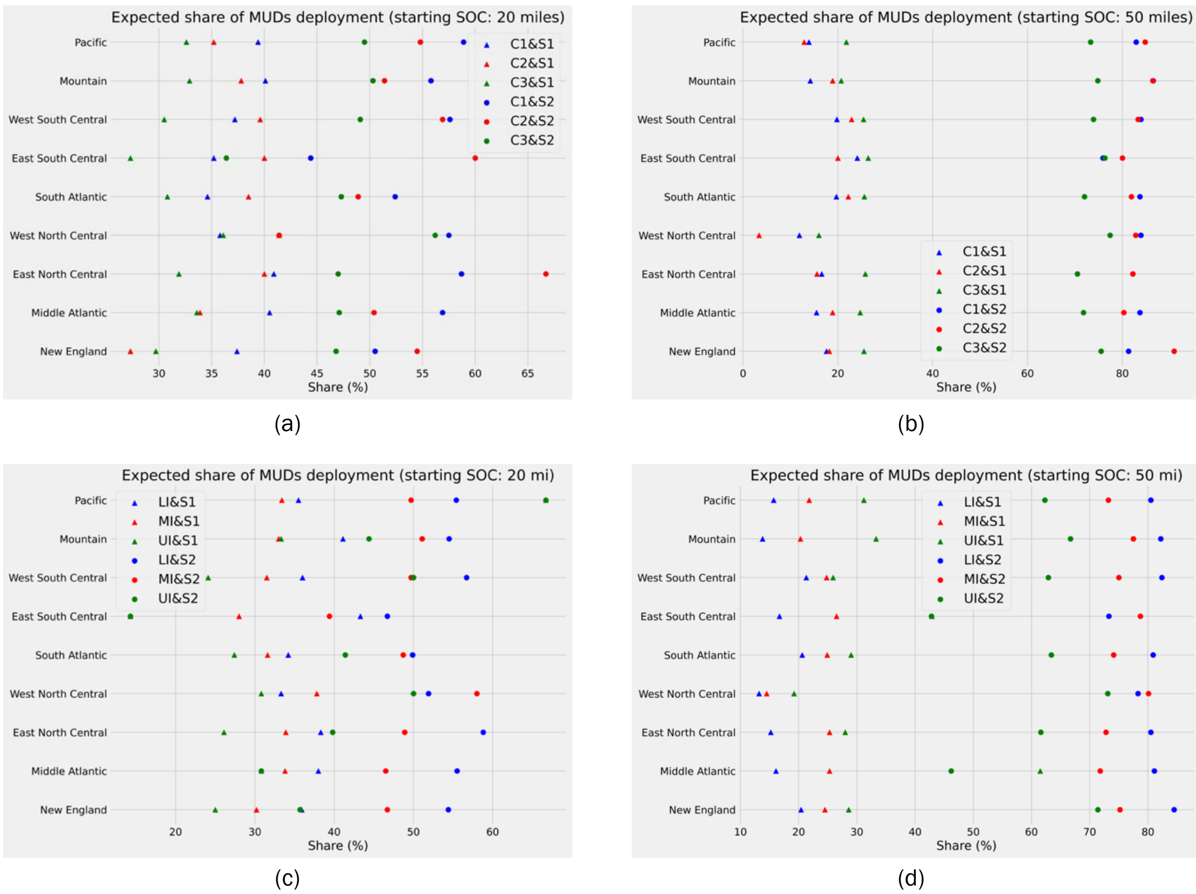


Figure I.20.3 MUDs charging stations expected deployment shares (a) starting SOC of 20 miles, (b) starting SOC of 50 miles, (c) starting at SOC of 20 miles and (d) at 50 miles for different locations. Source: University of Illinois at Urbana-Champaign

Subgraphs (a) and (b) of Figure I.20.3 show the expected deployment share of MUD charging stations, categorized for the three travel pattern clusters of MUD residents and drivers. On the other hand, subgraphs (c) and (d) show the MUD charging station expected deployment share for three different income groups (low, mid, and upper). Notice that C1 denotes cluster group 1 and LI, MI, and UI refer to lower income class, middle income class and upper income class, respectively. S1 denotes Scenario 1 of maintaining and ending the day with at least 20 miles of range, while S2 denotes Scenario 1 of ending the day with over 80 miles. Scenarios with higher state-of-charge at the beginning of each day result in a higher deployment share of MUD charging stations, since EVs at MUDs would require additional charging access during the day to meet the upper bound of the remaining driving range of 80 miles. Cluster 3 has the highest average VMT, while it also has the highest average dwell time at both public locations and workplace. EVs operated by drivers in cluster 3 tend to recharge at other stations. Since the initial range is just 20 miles in subgraph a, vehicles charge at the workplace and public stations to ensure that the comfortable driving range constraint is not violated. Therefore, cluster 3 travel needs can be satisfied with a lower MUD charging station share. However, in subgraph (b), under a scenario of electric vehicles starting their day with 50 miles of range, EV drivers decide to recharge at home in MUD hubs given the lower cost of charging at home locations and their greater flexibility to choose their charging location due to their greater range availability. Generally, the more VMT that need to be covered during the day the greater the MUD charging stations' share. In subgraph c, the upper income group has the lowest share of expected MUD charging station deployment when the EV battery needs to be significantly replenished (80 miles of range). This is because their dwell time at home is lower and, therefore they leverage public and workplace charging to meet such needs.

With the assumed deployment of a 7.2 kW level 2 charger on MUD premises, the estimated energy use by MUD chargers is shown in Figure I.20.4. As can be seen in subgraphs a, b, c, the energy use in the scenario where EVs need to meet a driving range of over 80 miles at the end of day is higher. Cluster 3 and the upper-income group use more daily MUD charging energy, since they cover more VMT daily. In subgraphs c and d, the lower-income group has the lowest energy use since vehicles cover less VMT daily and thus their charging time is expected to be briefer. Aggregating all the census divisions, for the scenario in which EVs start with 20 miles of range and maintain this comfort range at all times over the day (aligned with existing literature [18]), average per vehicle energy use varies from 10.98 to 20.49 kWh among the three clusters and three income groups. For the scenario in which EVs start the day with 50 miles of range and maintain a comfort range of 20 miles over the day, the average per vehicle energy use varies from 3.34 to 8.83 kWh. However, for the scenarios that require meeting 80 miles of range (i.e., SOC) at the end of the day, the average per vehicle energy use is substantially higher. When starting with 20 miles of range, the energy required per vehicle on a daily basis ranges from 43.75 to 50.67 kWh and when starting the day with 50 miles of range, the daily energy use per vehicle varies from 28.23 to 34.86 kWh.

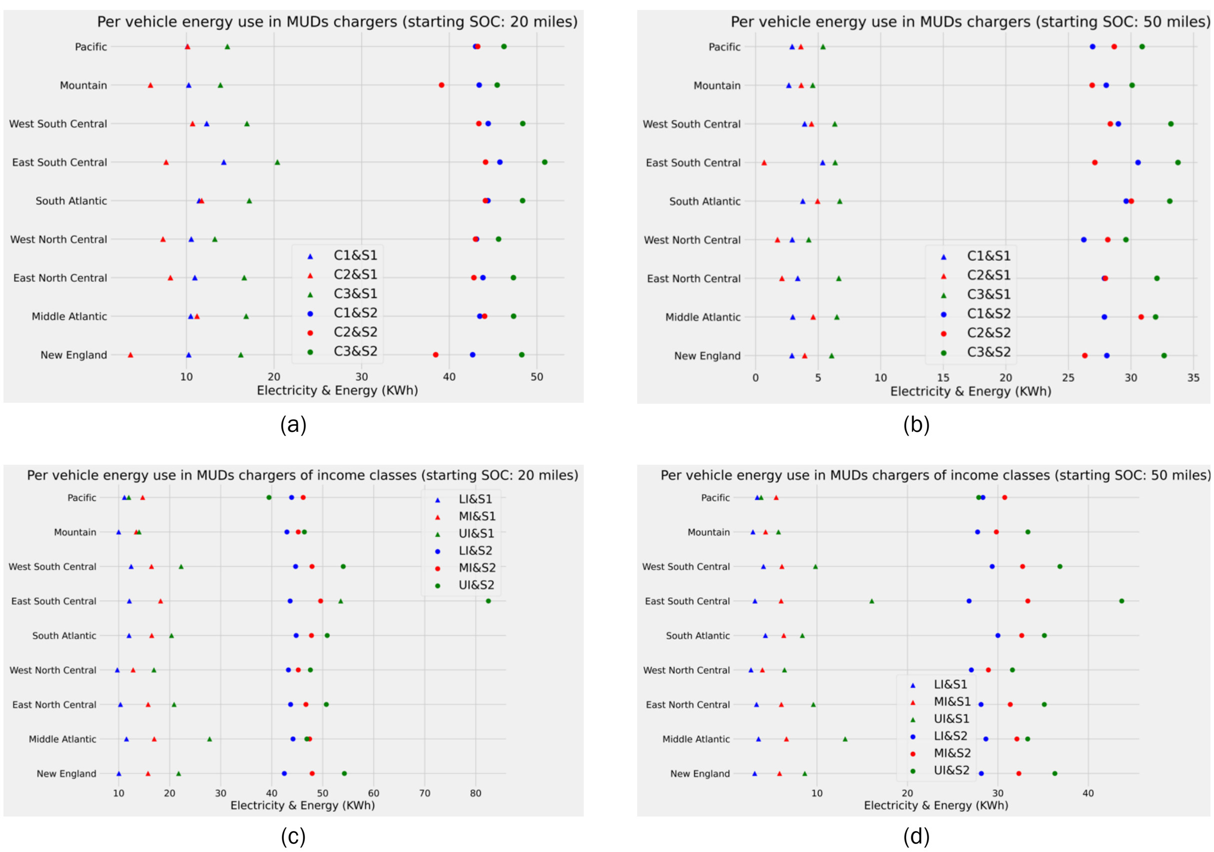


Figure I.20.4 Expected energy volume (in kWh) in MUDs chargers for (a) starting SOC of 20 miles, (b) starting SOC of 50 miles, (c) for income classes starting SOC of 20 miles, and (d) for income classes starting SOC of 50 miles. Source: University of Illinois at Urbana-Champaign

Conclusions

This analysis assesses the daily travel patterns of MUD residents based on the latest NHTS and AHS data. It presents the travel patterns of MUD residents and clusters of such residents generated by a hierarchical agglomerative clustering method as well as by income level categorization. Three clusters were identified, and their travel profiles (i.e., dwell time, VMT, etc.) are analyzed. A model is developed to estimate the need to deploy charging stations in MUDs and to simulate the charging decisions of MUD residents under a scenario of 100% light-duty vehicle electrification. For the cluster with the highest average daily VMT, charging availability in MUDs is the lowest when drivers start their day with 20 miles of range since they take advantage of workplace and public charging to meet their substantial travel needs, but is still needed since charging at home costs the least and dwell time at home is generally plentiful. The group from the lower income class requires a greater share of MUD charging but also charges less kWh daily due to lower levels of VMT. When an EV driver simply needs to ensure a comfortable mileage range of at least 20 miles, the energy used by MUD chargers could be as little as under 10 kWh, especially when the starting range is greater than 20 miles. For EV drivers who wish to recharge their vehicles to meet 80 miles of range at the end of the day, however, charging availability in MUDs is indispensable as, in these scenarios, the energy use at the residential MUD chargers is much higher, with the exact amount dependent on the starting range. The scenario exploring fully charging the MUD drivers' vehicles by the end of day (i.e., 80% SOC), consistently results in higher share of MUD charging station deployment, since drivers choose the cheapest home charging option to meet their operational needs.

Key Publications

Cheng, X. and Kontou, E. Travel Profile Clusters and Electric Vehicle Charging Needs of Multi-Unit Dwelling Residents. Under Review.

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Acknowledgements

DOE VTO sponsored this work under the Vehicle Technologies Analysis Program. The following DOE EERE managers played essential roles in establishing the project's concept, advancing implementation, and providing ongoing guidance: Jake Ward, Raphael Isaac, and Michael Ursic. The authors also acknowledge Xi Cheng, graduate student at the University of Illinois at Urbana-Champaign, as a major contributor to this research.

I.21 Energy Impacts of Electrified Passenger Air Transport (Argonne National Laboratory)

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Start Date: June 1, 2020 End Date: September 30, 2021
Project Funding (FY20–FY21): $150,000 DOE share: $150,000 Non-DOE share: $0

Project Introduction

Current estimates predict that aviation accounts for approximately 2% of total global emissions. However, this number is expected to rise to 12%–27% by 2050 [1]. This exponential rise in emissions is correlated with the steep rise in aviation demand. Air travel demand has tripled over the past 20 years and, according to pre-COVID-19 forecasts, was expected to double in the next two decades. Significant improvements have been made in aircraft technology to the point that travel energy efficiency, measured in megajoules per passenger kilometers traveled [2], is at par with light-duty vehicles, but business-as-usual future improvement will not be able to offset the increase in demand. Several avenues have been identified to help decarbonize aviation, but each has significant challenges in terms of both technological maturity and system integration. The primary methods being studied by academia and industry are sustainable aviation fuels, hydrogen propulsion, and electrification/hybridization. This project aims to evaluate the energy impacts of the latter. The steep reduction in battery cost combined with increasing battery-specific energy density has contributed to a rapid move toward hybridization and electrification in ground transportation (both passenger and freight). This maturation of electric propulsion has led to increasing research and interest into its viability in an aviation context. New generation aircraft like the B787 are designed to be “more-electric.” This move toward replacing hydraulic and pneumatic systems, which were powered by engine bleed air, with more efficient electric options has signaled a move toward hybridization and eventual electrification. Several companies are working on fully electric planes, and some commercial airlines have committed to add them to their fleet.

In recent years, startup companies and aerospace research organizations have led exploratory work into the design of several prototype electric vertical takeoff and landing (eVTOL) aircraft for carrying passengers in urban environments. The interest spawns from eVTOL aircraft showing great promise in saving commute times by flying over road traffic at high speeds. These aircraft can be used to create a new form of travel called Urban Air Mobility (UAM), which can shorten commutes and other cross-city trips dramatically. Additionally, this new mode of transportation may offer benefits by connecting suburban and rural communities to urban cores, thereby encouraging economic growth and development.

Objectives

The objective of this project was to evaluate at a high-level the potential energy impact of fully electric aircraft, both for intercity aviation and UAM under various technology improvement scenarios. This includes identification of the aircraft for which electrification is a viable, near-term option, estimating the energy consumption of such aircraft, both in a baseline and an electric-case scenario, and finally, estimating the demand in an UAM scenario.

Approach

To better understand the energy impact that all-electric aircraft can have on energy consumption, a two-step approach was used, as seen in Figure I.21.1, for both intercity aviation and UAM:

1. Electric aircraft modeling: Static aircraft models estimate range and energy consumption and can account for technological changes and efficiency improvements over time.

2. Passenger air travel demand modeling: For intercity aviation, we relied on the Bureau of Transportation Statistics 2019 database [3], which contains information on all U.S. domestic flights' origin-destination, distance, number of passengers, and aircraft type. For UAM, we used ACS [3] and Longitudinal Origin-Destination Employment Statistics (LODES) [4] datasets to develop an intracity commuter demand model for UAM.

Static aircraft performance models for both intercity aviation and UAM were constructed from existing literature. These models were subsequently used in conjunction with the demand models to predict energy and mobility impacts of electrified aviation.

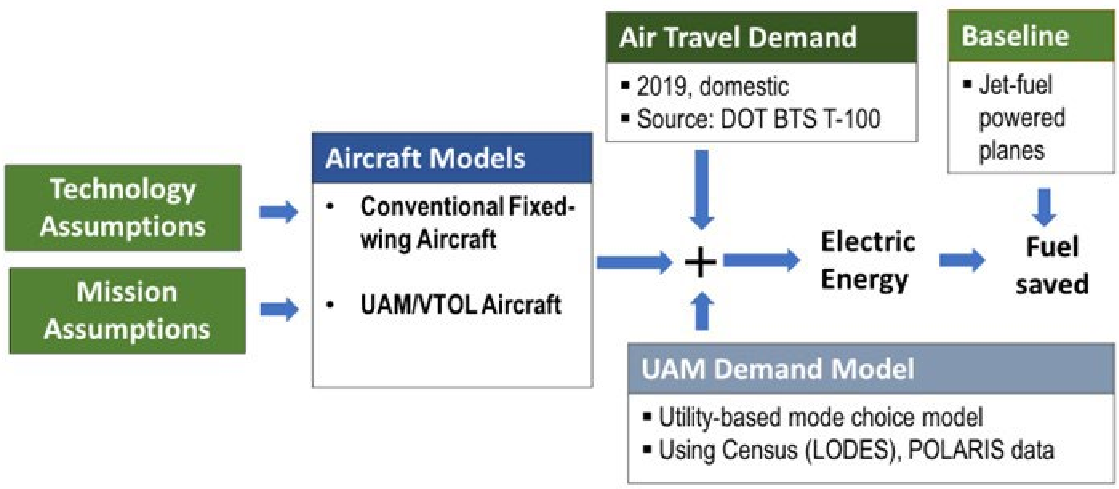

Figure I.21.1 Overview of the approach used to analyze the energy and fuel impacts of electrification of aviation. Source: ANL

Electrification of intercity passenger air travel

The aircraft models described just above were parametrized to obtain scenarios for three timelines—2030, 2040, and 2050—and to serve as references to characterize range and passenger capacity of the aircraft. Key technological assumptions like battery-specific energy, aerodynamic efficiency, powertrain efficiency, and power density were varied over these timelines. For each of the timelines, an electric and a conventional aircraft were designed for three different size classes. These classes were based on the number of passengers (pax) that a given aircraft can carry regardless of its range: 50 pax—20,000 kg maximum takeoff weight (MTOW); 100 pax—40,000 kg MTOW; 150 pax—80,000 kg MTOW. In each case, the categories served as constants to help calculate the different mass fractions for batteries (i.e., what percent of the total aircraft mass can be battery mass). The propulsive efficiency of the conventional powered aircraft was assumed to improve in future years, following a historical 1.5% per year increase rate.

Once the aircraft model specifications were calculated, a flight assignment based on the Bureau of Transportation Statistics 2019 data was carried out. Flights that are above the range and passenger thresholds of the largest aircraft (Class 3) were filtered out, while the remaining flights were deemed to represent viable opportunities for replacement by electric aircraft. For those remaining flights an aircraft class, depending on the flight distance and passenger occupancy for each departure, was then selected to carry out the flight.

Urban air mobility

Similarly, flight performance models for UAM vehicles were developed by using the existing literature and Open Vehicle Sketch Pad (OpenVSP) [5], which is a preliminary design software that can model the aerodynamics of a design. Two different eVTOL vehicles that are in advanced stages of design, the Joby S4 illustrated in Figure I.21.2 and the Lilium 7-seat aircraft, were modeled. For the Joby aircraft, multiple public-domain references [4]-[8] were employed to develop a model based on first-order physical relationships. For the Lilium aircraft, the modeling approach outlined in Lilium's recent white paper [11] was directly implemented.

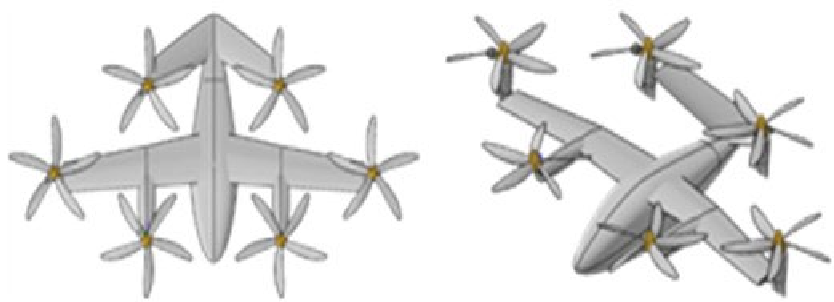

Figure I.21.2 OpenVSP model of the Joby S4 aircraft in hover configuration. Source: ANL

Case studies for the Atlanta and Chicago metropolitan areas were conducted in order to understand potential UAM commuting patterns. Both regions have extensive urban sprawl with densely populated suburbs and defined central business districts. This suggests that these cities could serve as early adopters for a commuter-based UAM service.

As a first step, the locations of the vertiports were determined using a vertiport placement model. This model provides a UAM infrastructure network that captures areas with high expected commuter demand. Following determination of the expected demand capture, the passenger choice model was used in conjunction with the LODES and ACS datasets to predict demand and usage patterns for the UAM service. Origin-destination pairs from the LODES dataset with the highest cost to society were identified, and their locations were clustered using a K-means clustering algorithm. The centroid location of each of these clusters was then used as the location for a vertiport. Through this method, vertiports were placed, in the model, in areas around a city and acted as origins or destinations for high-value commuter trips (top 100,000 highest income commuter trips).

Three different ticket prices, each representing a different stage of UAM development, were used to calculate the cost of using the UAM service. The selected prices were \$2.97/pax-mi, \$0.98/pax-mi, and \$0.47/pax-mi for the initial, near-term, and long-term scenarios, respectively, as determined by Uber [12]. The reductions in costs over time can be attributed to mature technologies that can take advantage of scaling in order to reduce operating and ownership costs. The cost of driving, for the purposes of comparison, was estimated using American Automobile Association, or AAA, 2020 average per-mile cost of \$0.64/mi [13].

Results

Electrification of intercity passenger air travel

The ranges for the different timelines, propulsion types, and classes are presented below in Table I.21.1. With 2030 assumptions, only the Class 3 aircraft is feasible when accounting for the safety and regulatory requirements, but its effective range is too short to be practical. Other smaller, commuter-class, viable aircraft could be designed with the 2030 technological assumptions, but they were not considered as part of this study as their large-scale impact on demand would be negligible.

Some collective results comparing electric aviation in 2040 and 2050 to aviation demand in 2019 are shown in Table I.21.2 and Figure I.21.3 below.

Table I.21.1 Ranges for Different Aircraft Based on the Static Performance Models

	2030 (0.5 kWh/kg)		2040 (1 kWh/kg)		2050 (1.5 kWh/kg)	
	Electric	Conventional	Electric	Conventional	Electric	Conventional
Class 1 (50 pax)	—	1,750 mi	230 mi	2,600 mi	620 mi	3,570 mi
Class 2 (100 pax)	—	1,835 mi	270 mi	2,800 mi	725 mi	3,960 mi
Class 3 (150 pax)	110 mi	2,630 mi	460 mi	3,975 mi	1,110 mi	5,650 mi

Table I.21.2 Collective Results Comparing Electric Aviation in 2040 and 2050 to Aviation Demand in 2019

	2040	2050
% of total departures	34%	65%
% of total distance	13%	44%
% of total passengers	26%	58%
% of total pax-miles	3.4%	25.5%
Fuel saved (tons)	468 million	1,207 million
Energy used (gigajoules)	116	272

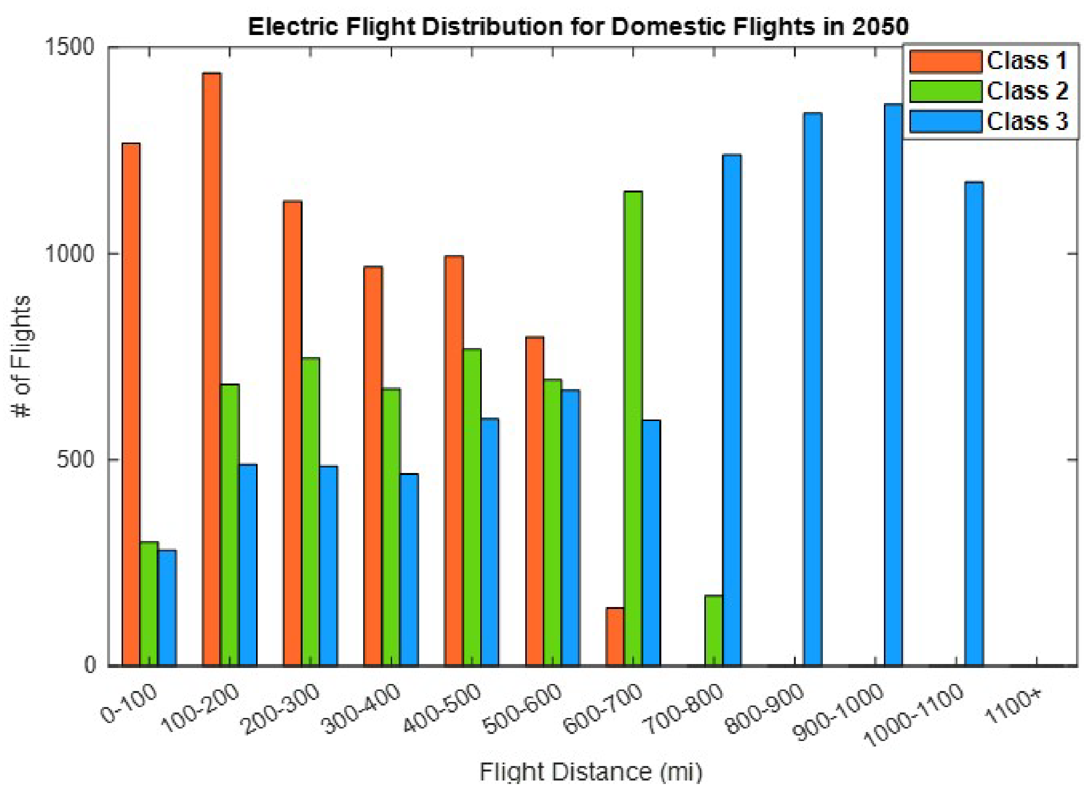

Figure I.21.3 Flight assignments of electric aircraft in 2050 for three different aircraft classes that could replace aviation demand (assuming 2019 levels). Aircraft classes are based on the number of passengers carried (i.e., maximum takeoff weight varies) regardless of range. Source: ANL

Urban air mobility

Figure I.21.4, which demonstrates simulated UAM usage for the long-term, high adoption case, shows a significant demand. At the ticket price of $0.47/mi, approximately 52% of the studied commuter population could be expected to use UAM travel in Atlanta, and approximately 78% of the high value commuter population in Chicago could be expected to use UAM travel. These patterns show a large proportion of users originating in the suburbs and commuting to the business districts. Additionally, the research finds that a significant number of trips are expected to occur between suburbs, which may not be as well connected to one another. The findings are encouraging signs for the viability of UAM as a transportation service. Even with a limited number of vertiports, large percentages of the studied populations found more utility from UAM than automobiles. It must be noted that these patterns have been estimated using a $0.64/pax-mi driving cost. Further research should factor in evolutions in driving cost in the context of greater penetration of electric vehicles.. Interestingly, project results show Chicago with higher adoption rates across all price ranges when compared to Atlanta. This could be attributed to the higher commute times experienced by residents of the Chicago metropolitan area. Both Chicago and Naperville, a sizeable suburb of Chicago, are ranked in the top 10 U.S. cities with the highest commute times, as reported by the U.S. Census Bureau [14]. As a result, residents may be more likely to use UAM to avoid congestion during commute times. This finding suggests that highly congested metropolitans would serve as ideal early adopters of UAM services. This is especially relevant in major U.S. cities that have high-density commercial and industrial activity concentrated at locations away from residential zones, which cause bottlenecks in existing transportation infrastructure.

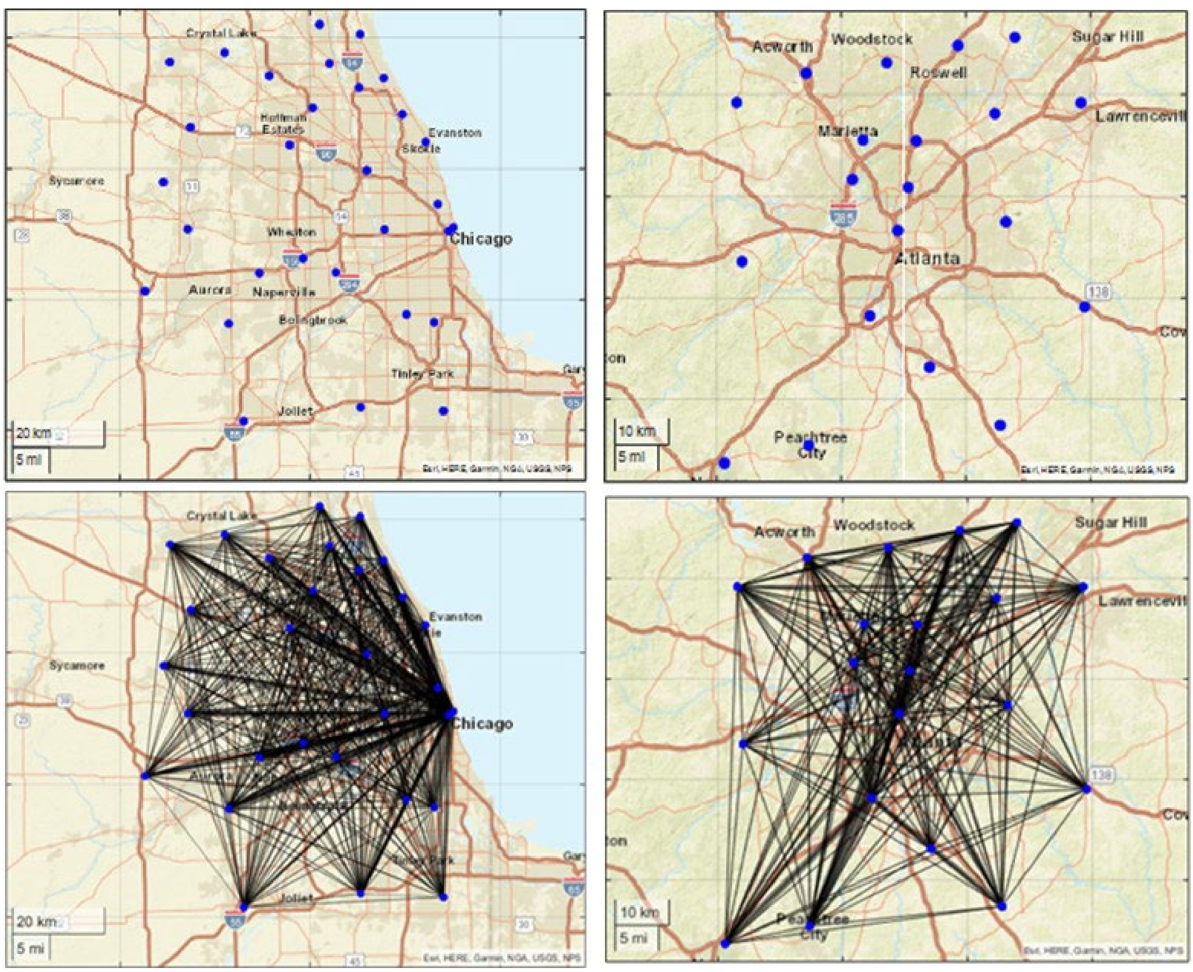

Figure I.21.4 UAM adoption rates at $0.47/mi (long-term estimate). Top left: Vertiport placement for Chicago. Bottom left: UAM trips at highest adoption rates for Chicago. Top right: Atlanta vertiport placement. Bottom right: UAM trips in Atlanta at highest adoption rates. Source: ANL

Conclusions

Electrification is a potential pathway for reducing aviation's carbon footprint. In this project, the first one within the VTO on the topic, the project team developed a new aviation modeling framework for passenger travel in order to quantify the potential impact of aviation electrification, stemming from both intercity travel and urban air mobility.

For intercity travel, this research has found that electrification and hybridization will first be introduced for short-haul aviation (<500 miles). In addition to being potentially carbon neutral, these technologies will also reduce the operational inefficiencies caused by using larger/longer-range aircraft for shorter flights. Electrification of longer flights might not be possible unless there are several breakthroughs in battery-specific energy (which is currently <1,500 Wh/kg). With major improvements in this area, and considering other technological advances, approximately a quarter of all passenger-miles could be performed on fully electric aircraft in 2050.

Urban air mobility will, according to the research findings, be concentrated among high-value customers or trips during its first rollout. However, it has the potential to be scaled to appeal to a larger base once lower operational cost and higher frequency become achievable.

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Acknowledgements

This work was performed in collaboration with Brian German and Ayush Jha, both of the Georgia Tech Center for Urban and Regional Air Mobility, CURAM.

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DOE/EE-2611 • August 2022