U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Analysis Program

2022 Annual Progress Report

Vehicle Technologies Office

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Disclaimer

Acknowledgements

We would like to thank all the principal investigators and their teams for contributing to this Annual Progress Report. Their hard work and ideas resulted in the success of the Vehicle Technologies Office Analysis Program and the office as a whole as well as enabling important improvements in fuel economy and the efficiency of the transportation system as a whole.

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

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Acronyms and Abbreviations

Symbols and Numbers

θ	symbol for road grade in the road load equation
ρ	symbol for air density in the road-load equation

A

a	acceleration
A	frontal area
ABM	agent-based model
ACT	Advanced Clean Truck
ACTIVSg70k	A 70,000 bus synthetic grid on the footprint of the eastern United States
ADOPT	Automotive Deployment Options Projection Tool
AEO	Annual Energy Outlook
AFDC	Alternative Fuels Data Center
ANL or Argonne	Argonne National Laboratory
ANSI	American National Standards Institute
APR	Annual Progress Report
ASTM	American Society for Testing and Materials
AT	autonomous technology
AV (or automated)	autonomous vehicle

B

BA	balancing authority
BAU	business-as-usual
BEAN	Benefit Analysis
BEV	battery electric vehicle
Biogeme	an open source Python package designed for the maximum likelihood estimation of parametric models in general with a special emphasis on discrete choice models
B/M	bastnasite/monazite
BOM	bill of materials

C

C_d	drag coefficient
Ci	Initial number of chargers
C_{rr}	coefficient of rolling resistance
C2G	cradle-to-grave
CaaS	Charging-as-a-Service

CAFÉ	Corporate Average Fuel Economy
CALSTART	North America’s leading advanced transportation technologies consortium
CAP	criteria air pollutant
CBG	census block group
CH_4	methane
CHTS	California Household Travel Survey
CI	compression ignition
CO	carbon monoxide
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalent
CPLEX	an optimization and solution management software for mathematical programming, such as linear programming, mixed integer linear programming, and general integer programming
CSTDM	California Statewide Travel Demand Model
CSFFM	California Statewide Freight Forecasting Model
CT	current term

D

D(X,t)	charging demand variable (a function of location and time of charging)
D.C.	District of Columbia
DCFC	direct current fast charger
DER	distributed energy resources
DER-VET	Distributed Energy Resources - Value Estimation Tool
DHL	Dalsey, Hillblom and Lynn
DOE	U.S. Department of Energy

E

EERE	Energy Efficiency and Renewable Energy
e.g.	for example
eGRID	Emissions and Generation Resource Integrated Database
EIA	U.S. Energy Information Administration
eMDHD	electric medium-duty/heavy-duty (vehicle)
EOL	end-of-life
EPA	U.S. Environmental Protection Agency
EPRI	Electric Power Research Institute
EV(s)	electric vehicle(s)
EVI-Equity	Electric Vehicle Infrastructure for Equity

EVI-OnDemand	Electric Vehicle Infrastructure for Demand of ride-hailing services charging infrastructure
EVI-Pro	Electric Vehicle Infrastructure Projection tool
EVI-RoadTrip	Electric Vehicle Infrastructure for Road Trips
eVMT	electric vehicle miles traveled
EVSE	electric vehicle supply equipment

F

FASTsim	Future Automotive Systems Technology Simulator
FCEV	fuel cell electric vehicle
FedEx	Federal Express
Fleet DNA	a clearinghouse of commercial vehicle operations data
FleetSeek™	a proprietary database of half a million North American trucking operations and contacts used by thousands of trucking product and service providers
FOTW	fact of the week
FY	fiscal year

G

g	gravitational acceleration (when referring to force)
g	grams (when referring to mass)
GA	Georgia
GEM	Grid-integrated Electric Mobility
GHG	greenhouse gases
GOOD	Grid Operation Optimized Dispatch
GREET®	Greenhouse gases, Regulated Emissions, and Energy use in Transportation
GREET1	Greenhouse gases, Regulated Emissions, and Energy use in Transportation (for fuel cycles)
GREET2	Greenhouse gases, Regulated Emissions, and Energy use in Transportation (for GHG emissions of vehicle production)
GridLAB-D	a power distribution system simulation and analysis tool
GUROBI	Problem solver for linear programming, quadratic and quadratically constrained programming, and mixed-integer programming
GW	gigawatt
GWh	gigawatt hour

H

H_2	hydrogen
HD	heavy duty
HDstock	heavy-duty stock (model)

HDT	heavy-duty truck
HDV	heavy-duty vehicle
HEV	hybrid electric vehicle
HEVII	Heavy-Duty Electric Vehicle Integration and Implementation
HEVI-LOAD	Heavy-Duty Electric Vehicle Infrastructure – Load Operations and Deployment
HFTO	Hydrogen and Fuel Cell Technologies Office
HOP	high oil price
HTSS(s)	hydrogen tank storage system(s)

I

ICE/ICEV	internal combustion engine/vehicle
i.e.	that is
ISATT	Integrated Systems Analysis Technical Team

J

JSP	job shop scheduling

K

kg	kilogram
kNN	k-nearest neighbor (in modeling)
kV	kilovolt
kW	kilowatt
kWh	kilowatt hour

L

LCA	life cycle analysis
LCFS	low-carbon fuel standard
LCI	life cycle inventory
LCOD	levelized cost of driving
LD(V)	light duty (vehicle)
LEM	Life Energy Motion
LiB	lithium-ion battery
LPG	liquified petroleum gas (or propane)
LT	long term

M

m	mass
MA3T	Market Acceptance of Advanced Automotive Technologies
MD	medium duty

MDHD/MDHDV or MHDV	medium- and heavy-duty vehicle
MDT	medium-duty truck
mi	mile
MMTCe	million metric tons of carbon equivalent
mph	miles per hour
MS	Microsoft
MSA	metropolitan statistical areas
MT	medium term
MUD	multi-unit dwelling
MW	megawatt
MWh	megawatt hour(s)
MY	model year

N

NCTCOG	North Central Texas Council of Governments
NEAT	Non-Light Duty Energy and GHG Emissions Accounting Tool
NEEDS	National Electric Energy Data System
NEI	National Emission Inventory
NHTS	National Household Travel Survey
Ni	nickel
NOx	oxides of nitrogen
N_2O	nitrous oxide
NREL	National Renewable Energy Laboratory

O

OBD	on-board diagnostics
ORNL	Oak Ridge National Laboratory

P

PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
PM2.5	particulate matter with aerodynamic diameters equal to or less than 2.5 micrometers
PM10	particulate matter with aerodynamic diameters equal to or less than 10 micrometers
POLARIS	Planning and Operations Language for Agent-based Regional Integrated Simulation - a high-performance, open-source agent-based modeling framework designed for simulating large-scale transportation systems

Pr(>|z|)	This represents the two-tailed p-values testing the null hypothesis that the coefficient is equal to zero (i.e., no significant effect). The usual value is 0.05 where none of the coefficients have a significant effect on the log-odds ratio of the dependent variable.
PV	photovoltaic

R

R&D	research and development
REE(s)	rare earth element(s)
REO(s)	rare earth oxide(s)
RISE	Routing and Infrastructure for Shared Electric

S

SHAEV	shared, automated electric vehicles
SCE	Southern California Edison
SCOOT	Screening for City Opportunities Online Tool
SHAEV	shared heavy-duty autonomous and electric vehicles
SI	spark ignition
SMART	Systems and Modeling for Accelerated Research in Transportation
SMR	steam-methane reforming
SO_2	sulfur dioxide
SP/RP	stated preference/revealed preference
ST	short term
SUV	sport utility vehicle
SVTRIP	Stochastic Vehicle TRIp Prediction

T

T3CO	Transportation Technology Total Cost of Ownership
TCO	total cost of ownership
TDP	Transportation Data Program
TEDB	Transportation Energy Data Book
TEEM	Transportation Energy Evolution Modeling
TITAN	Truck Integrated Techno-economic Analysis
TNC(s)	transportation network company(ies)
TRUCK	name of a model developed by NREL; not an abbreviation
TWh	terawatt-hour
TxDOT	Texas Department of Transportation

U

UPS	United Parcel Service

U.S.	United States
U.S. DRIVE	Driving Research and Innovation for Vehicle Efficiency and Energy Sustainability
USPS	United States Postal Service

V

v	vehicle speed
V	volt
VFCS	Verifiable Fuel Cycle Simulation
VISION	a model used to estimate the potential energy use, oil use and carbon emission impacts of advanced light- and heavy-duty vehicle technologies and alternative fuels through the year 2050
VMT	vehicle miles traveled
vs.	versus
VTO	Vehicle Technologies Office

W

W	watt
Wh/kg	watt hours per kilogram

X

xFC	extreme fast charging

Z

ZEV	zero emission vehicle

Executive Summary

During fiscal year 2022 (FY 2022), the U.S. Department of Energy Vehicle Technologies Office (VTO) funded analysis projects supportive of VTO's goals to pursue early-stage research in electric vehicles and mobility system technologies to reduce petroleum dependence, increase energy reliability and security, improve sustainable transportation affordability, and promote economic growth. VTO analysis projects result in a foundation of fundamental data, analytical models, and applied analyses that provide insights into critical transportation energy problems and assist in prioritization of research investments and portfolio planning.

This document presents a brief overview of VTO analysis efforts and progress for projects funded in FY 2022. Each of the progress reports includes project objectives, approach, and highlights of the technical results that were accomplished during FY 2022.

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Vehicle Technologies Office Overview

Vehicles move our national economy. Annually, vehicles transport 18 billion tons of freight—about $55 billion worth of goods each day[1]—and move people more than 3 trillion vehicle-miles.[2] Growing our economy requires transportation, and transportation requires energy. The transportation sector accounts for approximately 30% of total U.S. energy needs[3] and the average U.S. household spends over 15% of its total family expenditures on transportation,[4] making it, as a percentage of spending, the costliest 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 transportation sector has historically relied heavily on petroleum, which supports over 90% of the sector's energy needs today,[5] and, as a result, surpassed electricity generation to become the largest source of CO_2 emissions in the country.[6] The Vehicle Technologies Office (VTO) will play a leading role to decarbonize the transportation sector and address the climate crisis by driving innovation within and deployment of clean transportation technologies.

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; advanced materials for lighter-weight vehicle structures and better powertrains; energy-efficient mobility technologies and systems (including automated and connected vehicles as well as innovations in connected infrastructure for significant systems-level energy efficiency improvement); combustion engines to reduce greenhouse gas and criteria emissions; 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 R&D; Electrification R&D; Materials Technology R&D; Decarbonization of Offroad, Rail, Marine, and Aviation; Energy Efficient Mobility Systems; and Technology Integration. The Analysis group is part of VTO Operations. 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) 2022. The APR presents descriptions of each active project in FY 2022, including funding, objectives, approach, results, and conclusions.

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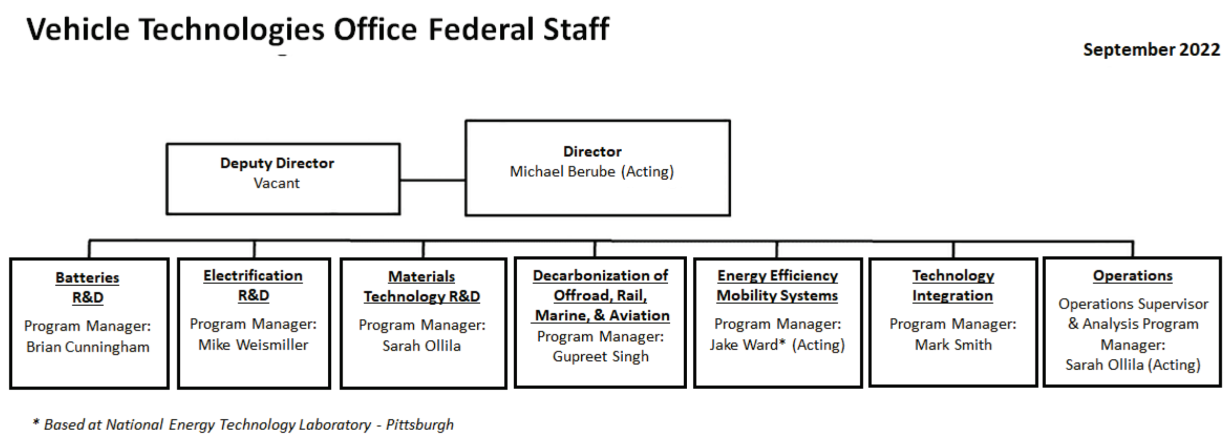
[1] Bureau of Transportation Statistics, DOT, Transportation Statistics Annual Report 2020, Table 4-1, https://www.bts.gov/tsar.
[2] Davis, Stacy C., and Robert G. Boundy. Transportation Energy Data Book: Edition 39. Oak Ridge National Laboratory, 2020, https://doi.org/10.2172/1767864. Table 3.8 Shares of Highway Vehicle-Miles Traveled by Vehicle Type, 1970-2018.
[3] Ibid. Table 2.2 U.S. Consumption of Total Energy by End-use Sector, 1950-2018.
[4] Ibid. Table 11.1 Average Annual Expenditures of Households by Income, 2019.
[5] Ibid. Table 2.3 Distribution of Energy Consumption by Source and Sector, 1973 and 2019.
[6] Environmental Protection Agency, Draft U.S. Inventory of Greenhouse Gas Emissions and Sinks, 1990-2019, Table 2-11. Electric Power-Related Greenhouse Gas Emissions and Table 2-13. Transportation-Related Greenhouse Gas Emissions.

Organization Chart



Analysis Program Overview

Introduction

Achieving deep decarbonization in transportation will require vehicle efficiency improvements, decarbonization of 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). The impacts of VTO's investments depend on the eventual commercialization of VTO-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. VTO Analysis projects also demonstrate additional capabilities and expertise provided by research partnerships that may include academia, the private sector, and non-profit organizations.

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 automation 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?
- What impacts will federal and state regulations (such as Environmental Protection Agency tailpipe and greenhouse gas emissions standards, National Highway Transportation Safety Administration Corporate Average Fuel Economy [CAFE] standards, or California Air Resources Board zero-emission vehicle mandates) have on VTO technology research priorities as well as the entire transportation ecosystem?

Goals

The goals of the VTO Analysis Program are to:

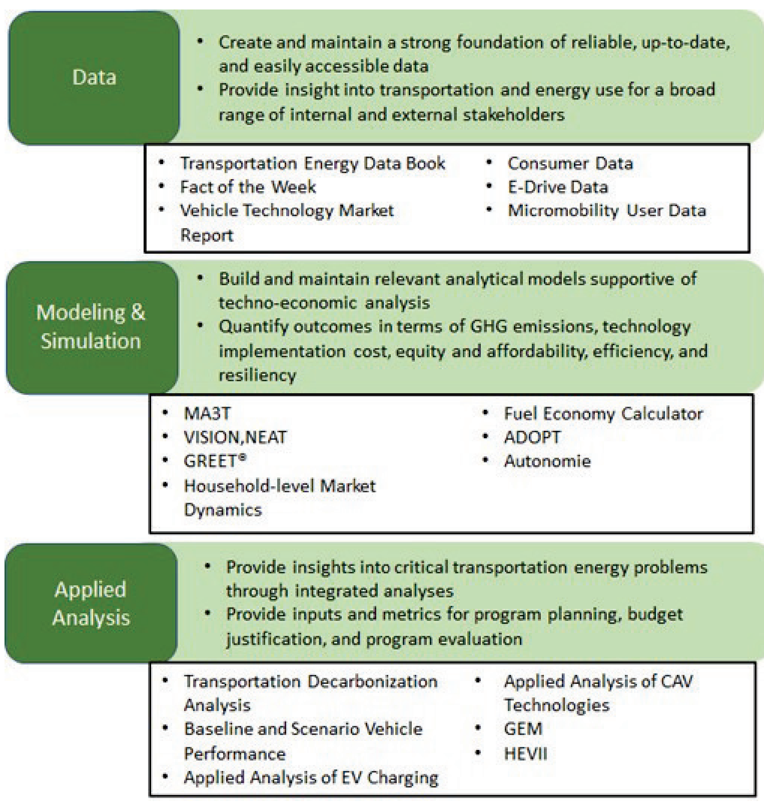
- Assist VTO in prioritizing technology investments and inform research portfolio planning.
- Support quantitative assessment of vehicle and mobility technology impacts.
- Provide insights into transportation and energy use problems for a broad range of internal and external stakeholders.

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 2022, 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.

I Technology and Market Data

I.1 Transportation Data Program (Oak Ridge National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (FY22): $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

The Transportation Energy Data Book and Vehicle Technologies Fact of the Week (FOTW) are created by Oak Ridge National Laboratory's (ORNL) Transportation Data Program (TDP) and serve to inform stakeholders, transportation analysts and Vehicle Technologies Office (VTO) staff, all of whom require quality current and historical data and related information on the transportation sector. The TDP provides a wealth of information that is used as a U.S. Department of Energy (DOE) resource to improve analyses of the transportation sector; these studies contribute to program planning, evaluation, and technology research in the public and private sectors. Meanwhile, stakeholders, academics, and others use these data to help move the United States toward reducing greenhouse gas emissions via shifts away from petroleum and other fossil fuels via increased mobility options, reduced single-occupancy vehicle travel, and increased electrification of the transportation sector.

Objectives

The objective of the TDP is to provide quality data and information for the VTO Analysis Program and stakeholders. Specifically, in fiscal year (FY) 2022, the project (1) produced the text, graphics, and data for a 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 are posted on the Transportation Energy Data Book website twice during the year, and (3) began a draft of Edition 41 of the Transportation Energy Data Book.

Approach

ORNL's approach for the TDP can be categorized into four stages: discovery, due diligence, approval, and publication, as illustrated in Figure I.1.1. Data are discovered (i.e., obtained) 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 National Laboratory and the National Energy Renewable Laboratory), government agencies (e.g., the Federal Highway Administration of the US Department of Transportation), and private companies (e.g., Ward's Automotive) to compile and understand the data that have been 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. VTO reviews and approves each FOTW as well as the tabulations and graphics in the Transportation Energy Data Book before final publication. The FOTW is published on the VTO Transportation Fact of the Week webpage (https://energy.gov/eere/vehicles/transportation-fact-week), and an email with the FOTW is sent via the GovDelivery system to the subscription list every week, typically on Monday afternoons. The PDF and MS Excel files for the Transportation Energy Data Book are posted on the website, which is hosted by ORNL (https://tedb.ornl.gov/). The major topics for the TDP publications are provided in Table I.1.1.

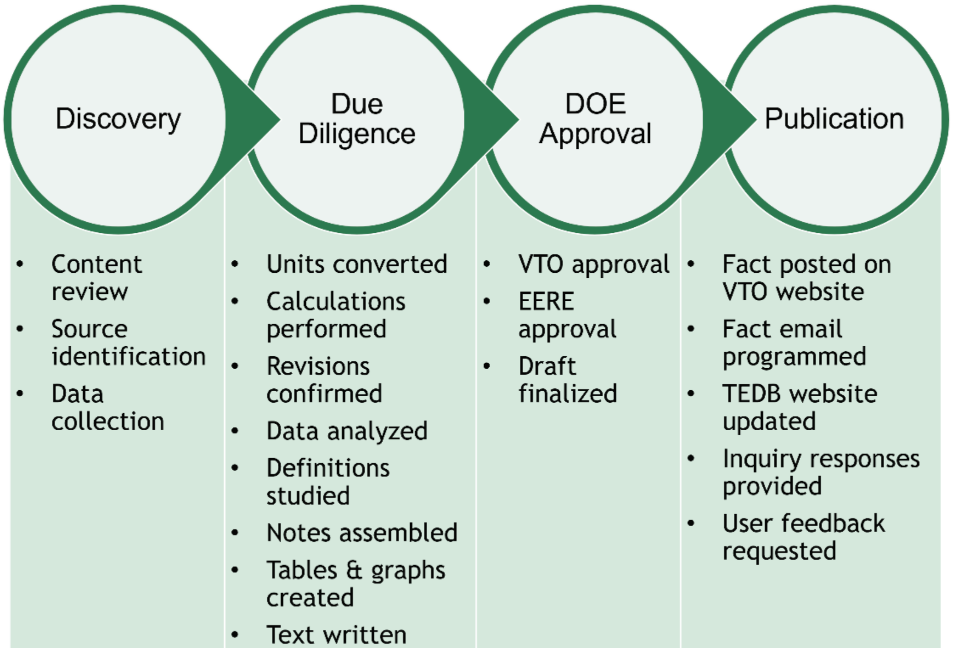

Figure I.1.1 Approach for the transportation data program at ORNL. Source: ORNL

Table I.1.1 Major Topics for the Transportation Data Program at Oak Ridge National Laboratory

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

Results

The weekly email for the FOTW began on July 27, 2015, with 50 email subscribers. As of the end of FY 2022, there were 22,550 subscribers to the newsletter.

FOTW 1206 through 1257 shown in Table I.1.2 were posted on the VTO website during FY 2022. For the FY 2022, FOTW content accounted for 1,911,837 pageviews, or 61% of all VTO website pageviews during the FY. Of those pageviews, 914,805 were unique visits, meaning that some visitors (997,032) to FOTW content were repeat visitors. Of all VTO website visits, 28% (890,575) 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—743,939, or 24% of all website pageviews during the FY.

Table I.1.2 Facts of the Week Posted on the VTO Website in FY 2022

Date Posted	Fact Title
09/26/2022	Seventeen EV Models Achieved an EPA Combined Rating of 100 MPGe or Higher in MY 2022
09/19/2022	Per Capita Transportation Energy Use Across the 50 States Ranged from 25 to 225 Million Btu
09/12/2022	Hybrid-Electric SUVs' Share of Light-Duty Vehicle Production Nearly Doubled from MY 2020-21
09/05/2022	2021 Hybrid-Electric Vehicle Sales Increased by 76% over 2020
08/29/2022	Fourteen MY 2022 Light-Duty Electric Vehicle Models Have a Driving Range over 300 Miles
08/22/2022	Advanced Technology Vehicles Gain Production Share from Conventional Gasoline Vehicles
08/15/2022	Electric Vehicles Have the Lowest Annual Fuel Cost of All Light-Duty Vehicles
08/08/2022	U.S. 12-Month Vehicle Travel for March 2022 Matched the December 2019 Total
08/01/2022	Since April 2020, Average Used Light-Duty Vehicle Prices Have Been Volatile
07/25/2022	The Average U.S. Household Spent Nearly $10,000 on Transportation in 2020
07/18/2022	Transportation Contributed 8% to U.S. Gross Domestic Product in 2020
07/11/2022	Cumulative Plug-in Vehicle Sales in the United States Reached 2.6 million in April 2022
07/04/2022	EPA Estimated Annual Fuel Cost for MY 2022 Light-Duty Vehicles Ranges from $500 to $8,250
06/27/2022	In Most States the Average Retail Price for Residential Electricity was <15 Cents per KWh
06/20/2022	Twenty-Two Percent of MY 2022 Light-duty Vehicle Models Require Premium Fuel
06/13/2022	Production Capacity of Renewable Natural Gas Projects was 574 million DGE in 2021
06/06/2022	Choosing the Right Vehicle for Your Next Road Trip Can Save Fuel and Money
05/30/2022	Slow Down to Save Fuel: Fuel Economy Decreases 27% When Traveling at 80 mph Versus 60
05/23/2022	Idling an Engine for as Little as 10 Seconds Uses More Fuel than Stopping and Restarting
05/16/2022	The Avg Nationwide Monthly Gas Price Was Highest in July 2008 When Adjusted for Inflation
05/09/2022	Fuel Economy for All Vehicle Classes Has Improved Substantially Over the Past Two Decades
05/02/2022	In 2021, 12.5% of New Light-Duty Vehicle Registrations in CA were Plug-in Electric Vehicles
04/25/2022	Motor Vehicles Were the Top Commodity by Value Shipped from Seven States
04/18/2022	Volumetric Energy Density of Li-on Batteries Increased by More than 8 Times from 2008-2020
04/11/2022	Texas Leads the Nation in Both Crude Oil Production and Electricity Generation
04/04/2022	Net Petroleum Imports to the United States Continue to Decline
03/28/2022	Over Half of U.S. Petroleum Imports in 2021 Came from Canada
03/21/2022	More than Half of all Daily Trips Were Less than Three Miles in 2021

03/14/2022	Number of Daily Trips Taken by Americans in 2021 Rebounded from 2020 Lows
03/07/2022	Cobalt is the Most Expensive Material Used in Lithium-ion Battery Cathodes
02/28/2022	Light-Duty Plug-in Electric Vehicle Sales in the United States Nearly Doubled from 2020 to 2021
02/21/2022	Manufacturers Are Adopting a Wide Array of Vehicle Technologies that Improve Fuel Economy
02/14/2022	From 2016-2019, over 90% of U.S. Lithium Imports Came from Argentina and Chile
02/07/2022	Average Horsepower Reaches All-Time High for MY 2021 Light-Duty Vehicles
01/31/2022	Average Carbon Dioxide Emissions for 2021 MY Light-Duty Vehicles at an All-time Low
01/24/2022	Light-Duty Vehicle Sales For 2021 Were 3% Higher than 2020
01/17/2022	MY 2021 All-Electric Vehicles Had a Median Driving Range of 60% That of Gas Powered Vehicles
01/10/2022	In MY 2021 the Electric Vehicle with the Longest Range Reached 405 Miles on a Single Charge
01/03/2022	Residential Parking Options and Access to Electricity Will Impact Electric Vehicle Adoption
12/27/2021	Study Shows Transit Buses Idle for an Average of 3.7 Hours per Day
12/20/2021	Thirteen New Electric Vehicle Battery Plants Are Planned in the U.S. Within the Next Five Years
12/13/2021	Plug-in Vehicles' Share of New Light Duty Vehicle Sales in Europe More than Tripled in 2020
12/06/2021	Data from the 1st Quarter of 2021 Show Nearly 10,000 Workplace Chargers Were Installed
11/29/2021	Electric and Fuel Cell Heavy Trucks Could Have Lower Total Cost of Ownership Than Diesels
11/22/2021	Education about Electric Vehicles Increases Likelihood Buyers Will Consider Purchasing Them
11/15/2021	High Adoption of Shared Micromobility in the U.S. Can Save 2.3 billion GGE per Year
11/08/2021	Energy Zones Mapping Tool Allows for Locating New EV Charging Stations with Equity Considerations
11/01/2021	Sixty Percent of DC Fast Charging Ports Had Power Levels >50 kW in the First Quarter of 2021
10/25/2021	CA, WA, and HI Had the Highest Share of Transportation-Related CO2 Emissions in 2018
10/18/2021	Life Cycle GHG Emissions for a 2020 Electric Small Sport Utility Vehicle Were ½ Those of a Conventional One
10/11/2021	The South-Central Region Had the Highest Share of Heavy-Duty Diesel Trucks Equipped with Technologies to Reduce NOx and PM
10/04/2021	DOE Estimates That Electric Vehicle Battery Pack Costs in 2021 Are 87% Lower Than in 2008

The Transportation Energy Data Book is an online publication that is published once per year with mid-year updates to the tables and graphics. The final Edition 40 was approved by DOE and published in April 2022. An update to Edition 40 debuted online at the end of June 2022, with 48 tables and three figures updated with more recent data than was published in the original Edition 40. Additional tables and figures were updated in preparation of Edition 41, which will be posted to the website in FY 2023, once DOE has reviewed and approved the content. A LinkedIn Live Event centered around the 40th edition of the Transportation Energy Data Book was hosted by EERE and posted on YouTube afterwards. The event was planned, practiced, and executed with Dave Howell, VTO Director, serving as the moderator. Stacy Davis and VTO's Mark Smith, standing in for VTO Analysis Program Manager Jake Ward, answered questions.

The Transportation Energy Data Book 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 several times a year. Other pages on the website provide access to an archive of older reports, citation information, and project contact information. The Transportation Energy Data Book website had 47,247 pageviews in FY 2022. Google Scholar reports a total of about 4,110 citations for the Transportation Energy Data Book and 226 citations for Edition 40 as of December 2022.

Data collected in the TDP have also provided input to other VTO programs and other agency models, such as ORNL's Market Acceptance of Advanced Automotive Technologies (MA3T) model, ANL's Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET®) model, NREL's Automotive Deployment Options Projection Tool (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 (MOVES) model.

Conclusions

The 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, evaluation, and technology research to address transportation and mobility goals, including reducing petroleum dependence, single-occupancy vehicle travel, and greenhouse gas emissions.

Key Publications

1. Davis, S. and R. Boundy. 2022. "Transportation Energy Data Book: Edition 40." Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Acknowledgements

Robert G. Boundy of Roltek, Inc., provided TDP support.

I.2 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): $880,000	Project Funding (Initial): $880,000	Non-DOE share: $0
Project Funding (FY22): $200,000	Project Funding (FY22): $200,000	Non-DOE share: $0
Total Project Funding: $1,080,000	DOE share: $1,080,000	Non-DOE share: $0

Project Introduction

The Department of Energy (DOE) Vehicle Technologies Office (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, intending to assess the potential benefits of VTO-supported technologies and to evaluate program activities. Major challenges have included the lack of readily available historical data in the United States and other markets, along with a limited geospatial understanding of advanced vehicle sales trends, mobility trends, and consumer choice within the United States. A systematic examination of regional electric drive vehicle purchase trends and mobility usage patterns enables high-quality support and guidance for national impact analyses (e.g., potential energy and emissions reductions) 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, growing electric vehicle use can offset petroleum consumption associated with conventional internal combustion engine vehicles.

Advanced vehicle technologies covered in this study include electric drive vehicles, shared mobility (i.e., transportation network companies [TNCs], bikeshare, scooter share, etc.), and connected and automated vehicles. Electric drive vehicle technologies include hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs).

Objectives

The main objective of this project was 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 included the following tasks:

- Electric drive vehicle sales tracking: Collect monthly plug-in electric vehicle (PEV), HEV, and fuel cell electric vehicle sales data, by make and model, and summarize the market and technology trends.
- PEV national and regional impact assessment: Quantify the national impact of PEV adoption on an annual basis.
- Electric vehicle lithium-ion battery (LiB) supply chain tracking: Summarize historical and future LiB cell and pack production by manufacturer and by vehicle make and model.

- New mobility technologies tracking: Summarize shared mobility data availability and trip trends by region and mobility type.

This project provided quality data and information on electrification and new mobility technologies to the VTO Analysis Program and to external researchers. Deliverables included monthly and annual public-facing reports, with selected data published on the Argonne National Laboratory (Argonne) website.

Approach

There were four tasks under this project. Below are descriptions of the methods for individual tasks.

Electric Drive Vehicle Sales and Registration Tracking

This task involves collecting monthly electric drive vehicle sales data by manufacturer and model from various resources (websites and data subscriptions; not owners) and at different points in time. The research team summarized the observed market trends and technology evolution of electric drive vehicles in a monthly report that was distributed to DOE and national laboratory researchers. Because the data source is proprietary, aggregated information was distributed to the public subscribers. Argonne also published selected data on the following webpage to improve public awareness: https://www.anl.gov/es/light-duty-electric-drive-vehicles-monthly-sales-updates. This task also involved collecting and summarizing vehicle registration data for detailed spatial analysis for light-duty vehicles of all powertrains. For electric drive vehicles, registration information was summarized quarterly at the state level for use by DOE staff. The zip-code-level registration data enables analysis based on demographic profiles for equity analysis, considering zip codes with lower incomes, low access to transportation, or other socioeconomic indicators of interest.

PEV National and Regional Impact Assessment

In this task, the project team conducted a national-scale evaluation of PEVs on an annual basis and summarized the evaluation in a public-facing report. The report that was produced includes both national-scale metrics, such as aggregate electricity consumption and gasoline consumption reduction, and vehicle-level metrics, such as average vehicle performance. This report also demonstrates the evolution of PEV characteristics such as sales-weighted electric range and energy consumption per mile. Such information was additionally used to inform numerous analyses inside and outside of DOE; for example, these data were used to estimate the number of batteries available for recycling in the United States.

This task also informed evaluations of regional similarities and differences within the homogeneous PEV market, specifically regionally variable PEV energy consumption profiles.

Electric Drive Vehicle LiB Supply Chain Tracking

Using the PEV sales data collected, this task summarized the historical battery cell and pack production, by manufacturer and production location, of the PEVs sold in the United States. This task tracked original equipment manufacturer announcements about LiB investment and expected annual production in the United States and other regions. This information was then used to provide responses to internal and external queries about LiB investment needs (e.g., production capabilities and raw materials needed) to support transportation decarbonization.

New Mobility Technologies Tracking

This task summarized shared mobility data availability and trip trend by region and mobility type, including TNCs, shared bikes, and shared scooters. Based on the data collected, this task also involved conducting an analysis using mobility data for the city of Chicago as an example of how mobility usage varies by household income and vehicle ownership.

Results

Through December 2021, over 2.3 million PEVs had been sold in the United States, with 1.3 million of these BEVs and 800,000 PHEVs which can use gasoline. In 2021, the sales-weighted average range for BEVs reached 290 miles and, for PHEVs, reached 28 miles. This research team estimates that electric vehicles have driven 68 billion miles on electricity since 2010, reducing national gasoline consumption by 0.54% in 2021, and reducing consumption by 2.5 billion gallons cumulatively through 2021. In 2021, PEVs used 6.1 TWh of electricity to drive 19.1 billion miles, offsetting 690 million gallons of gasoline including use by PHEVs. This fuel-switching to electricity reduced consumer fuel costs by a collective $1.3 billion dollars in 2021. Since 2010, 64% of PEVs sold in the United States have been assembled domestically, and over 110 GWh of LiBs have been installed in vehicles to date. Table I.2.1 summarizes the high-level national impacts of these PEVs, including PEV sales, electric vehicle miles traveled (eVMT), gasoline displacement, electricity consumption, and reductions in carbon dioxide emissions in each year, each from 2011 to 2021. A report released in 2022 by the research team documents the details of the methodology used to estimate eVMT, weighted efficiency, and the resulting gasoline displacement [1].

Table I.2.1 Annual Sales of New PEVs, Total Annual eVMT, Gasoline Reduction, Electricity Consumption, and CO_2 Emissions Reduction Due to On-Road PEVs

Year	PEV Sales (thousands)	eVMT (billion miles)	Gasoline Reduction (million gallons)	Electricity Consumption (gigawatt-hours)	CO_2 Emissions Reduction (million metric tons)
2011	18	0.1	3	30	0.02
2012	53	0.3	13	100	0.08
2013	97	0.9	40	330	0.27
2014	119	1.8	73	610	0.50
2015	114	2.9	120	990	0.81
2016	160	4.0	160	1,400	1.10
2017	196	5.6	220	1,900	1.60
2018	331	8.3	310	2,800	2.30
2019	320	11.7	430	3,800	3.30
2020	308	13.0	480	4,200	3.70
2021	634	19.1	690	6,100	5.40
Total	**2,350**	**67.8**	**2,500**	**22,000**	**19.10**

Calculating the exact magnitude of decarbonization from switching from petroleum-based fuel combustion to grid-derived electricity is complex. Variations in local grid mixes lead to differing carbon intensities of electricity in different regions. This complexity is compounded by geographical differences in vehicle characteristics. The regional assessment considers these geographic differences to produce a historical assessment of PEV fuel cycle carbon emissions in the United States from 2011 to 2021 [2]. We find that PEVs in the United States decreased in electricity-derived carbon intensity from 2011 to 2021, from 187 grams per mile to 110 grams per mile, because of improvements in the electric grid and vehicle efficiency. This can be seen in Figure I.2.1. In the figure, the blue line represents the greenhouse gas (GHG) emissions rate since 2011, assuming a nationally uniform distribution of PEV registrations (or equivalently, a nationally uniform electricity grid); The orange line represents the national average emissions rate, accounting for regional variations in the distribution of electric vehicle registrations along with differences in the emissions rates for utility-generated electricity from the Emissions & Generation Resource Integrated Database (eGRID) [3]; The black line accounts for distributed solar electricity when determining the electric emission rates. All three methods of estimating the GHG emissions show a downward trend from 2011 to 2021, indicating the simultaneous environmental improvements of the electricity grid and improved vehicle efficiency, with most of the benefit coming from the reduced carbon intensity of the electric grid. For each curve, the reduction in GHG emissions has been approximately 40% over the last decade.

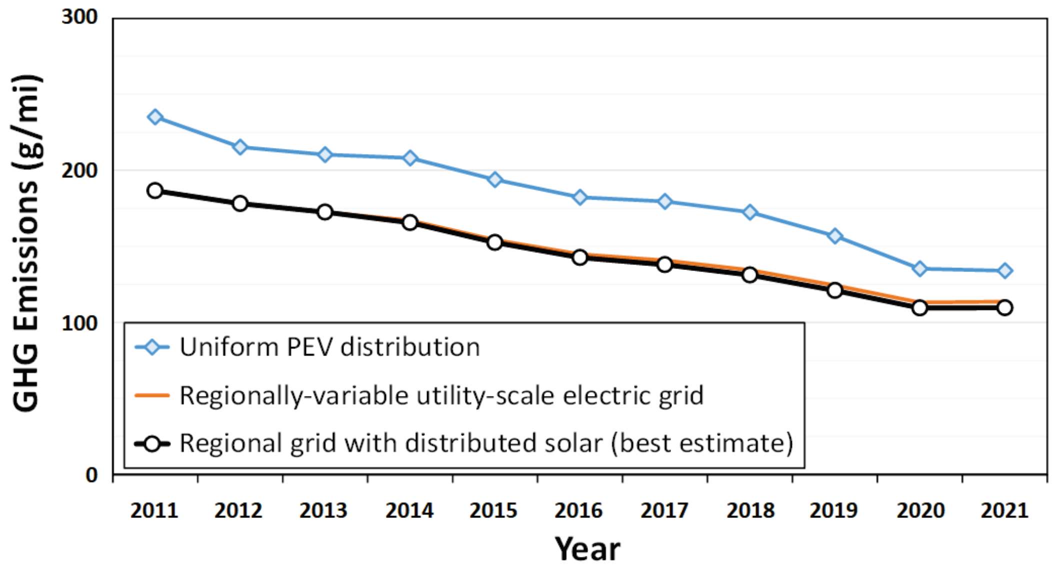

Figure I.2.1 Comparison of average well-to-wheels GHG emissions weighting for all registered PEVs in the United States from 2011 to 2021. The blue line represents a uniform national distribution of vehicles and electricity generation, the orange line accounts for the spatial distribution of vehicle registrations, and the black line includes the impacts of distributed solar generation. Source: Argonne

Over the same distance, comparable gasoline vehicles would have emitted between 29 and 41 million metric tons of GHG, so the switch to PEVs has led to a reduction of 15 to 27 million metric tons—a 13% greater reduction in GHG emissions than previously calculated in national-level assessments that do not factor in this regional difference. Future announced goals to further decarbonize the electricity sector will lead to actions that continue to reduce PEV emissions, including reducing emissions rates for vehicles already on the road, further improving the benefits relative to contemporaneous gasoline vehicles.

Understanding the battery supply chain is particularly important for the strategic planning and development of a battery recycling infrastructure to secure critical materials supply. Argonne recently published a comprehensive assessment of the LiB supply chain for PEVs in the United States [4]. Following the methodology in that report, we summarize, below, the manufacturing and production locations of LiB cells and packs, by make and model, for PEVs sold in the United States from 2010 to 2021. Figure I.2.2 shows a Sankey flow diagram for the manufacture of PEVs sold in the United States, including production locations of battery cells and battery modules and final assembly location, in terms of total battery capacity in gigawatt-hours. For most vehicles, the supply chain has been regionalized; European cell production often led to assembly of the packs and final vehicles in Europe as well. Many Asian cells have been imported to North America for assembly into U.S.-made packs and U.S.-assembled vehicles. This analysis indicates that the batteries used in PEVs sold in the United States have been largely domestically sourced. From 2010 to 2021, over half of all PEVs sold in the United States have cells that were produced domestically, as have over 70% of all battery packs in these vehicles. In terms of total energy capacity (in Watt-hours) for domestically sold PEVs, 57% of battery cells have been manufactured and 84% of battery packs have been assembled in the United States. These percentages are larger than the share for vehicles, as domestically produced PEVs have higher-capacity batteries, on average. In 2021, again for US-sold PEVs, 65% of battery cells and 73% of battery packs were domestically produced, with the majority of domestic production being used in Tesla vehicles. The Inflation Reduction Act, passed by the U.S. Congress in 2022 and signed into law shortly, thereafter, established a clean vehicle tax credit to go into effect in 2023; for each make and model, eligibility for that tax credit is tied to the North American value of battery component manufacturing and assembly.

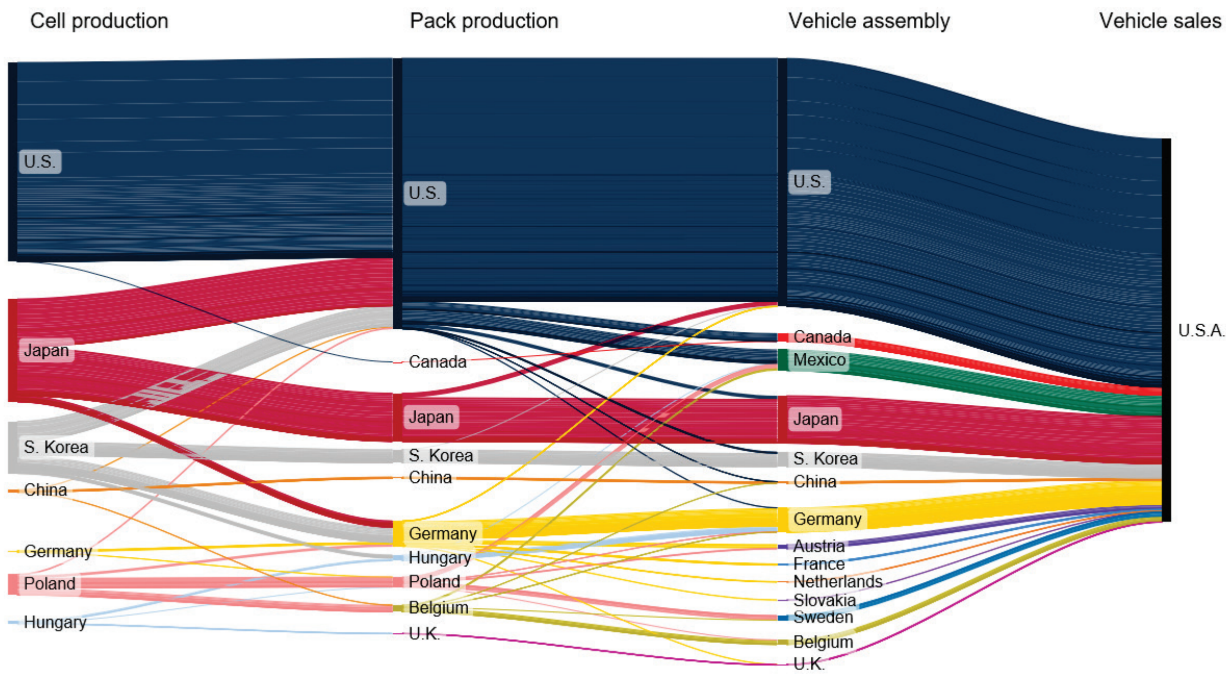

Figure I.2.2 Sankey flow diagram showing manufacturing locations for cells, packs, and vehicles for PEVs sold in the United States from 2010 to 2021 (in terms of total battery capacity in gigawatt-hours). Source: Argonne

The analysis for the fourth task listed above evaluates shared mobility technology usage in the context of household income and an average number of household vehicles by census tract. 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 Figure I.2.3, the analysis also found that census tracts with higher household incomes and fewer household vehicles tend to have higher TNC usage per capita, and similar trends are seen with bikeshare and scooter share usage. The single group with the highest TNC use is high-income households with fewer than one vehicle, a group that averages nearly 1.5 TNC rides per person per day. The highest-income group has the greatest variation in usage and, in general, the higher the group income, the more variation in TNC usage.

The boxplot in Figure I.2.3 shows the variation in TNC trips per capita for a given income bracket, split into four quantiles, for the number of household vehicles available. Each census tract in Chicago is included as one data point in the boxplot. Each boxplot shows the median (horizontal line) and spread of the TNC trips per capita for all census tracts within the indicated income bracket along the horizontal axis and the mean household vehicles bracket, indicated by a color key. Note that an inset is included for the lowest income brackets to better show the variation in the data.

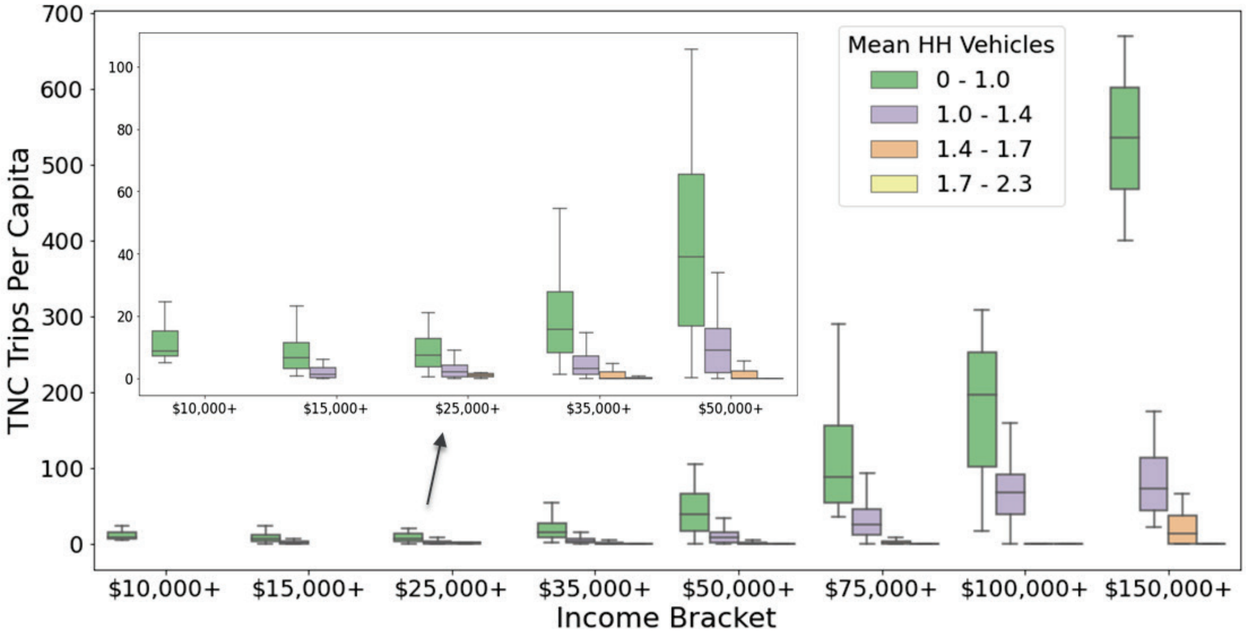

Figure I.2.3 Distribution of TNC ridership by household income and vehicle ownership. Source: Argonne

Conclusions

Between 2010 and 2021, over 2.3 million PEVs have been sold in the United States. These vehicles have been driven nearly 70 billion miles, displacing more than 2.5 billion gallons of gasoline, preventing nearly 20 million metric tons of GHG, and consuming 22 TWh of electricity nationally. Regional PEV assessment improves upon these estimates by calculating emissions using a weighted average that accounts for where electric vehicles are driven, resulting in a 13% decrease from the previously calculated values, which relied on a national average electricity emissions intensity.

Most of the PEVs on the road were assembled in the United States, and many of the battery packs and cells were built domestically as well. Nearly two-thirds of PEVs have been assembled in the United States, and 40% of the total content is domestically sourced. Over 110 GWh of battery capacity has been installed in PEVs since 2010, with nearly half of this total occurring since 2020. Automakers and battery companies have announced construction of battery factories across the world, including in North America, aiming to satisfy projected growth in PEV sales.

Key Publications

1. Gohlke, David and Yan Zhou. 2022. *Assessment of Light-Duty Plug-in Electric Vehicles in the United States, 2010–2021.* Argonne National Laboratory, Report ANL-22/71. https://doi.org/10.2172/1898424.

2. Gohlke, David, Xinyi Wu, Jarod Kelly, Logan Hennes, and Yan Zhou. 2022. *Regional Variation in Light-Duty Plug-in Electric Vehicle Emissions.* Argonne National Laboratory, Report ANL-22/34. https://www.osti.gov/biblio/1876832.

3. Rush, Luke, Matthews Cribioli, David Gohlke, Yan Zhou, Jarod Kelly, and Xinyi Wu. 2022. *Shared Mobility Data Availability and Usage Trends.* Argonne National Laboratory, ANL/ESD-22/9. doi:10.2172/1867694.

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1. Gohlke, David and Yan Zhou. 2021. *Assessment of Light-Duty Plug-in Electric Vehicles in the United States (2010–2020)*. Argonne National Laboratory, Report ANL/ESD-21/2. https://doi.org/10.2172/1785708.

2. Gohlke, David, Xinyi Wu, Jarod Kelly, Logan Hennes, and Yan Zhou. 2022. *Regional Variation in Light-Duty Plug-in Electric Vehicle Emissions*. Argonne National Laboratory, Report ANL-22/34. https://www.osti.gov/biblio/1876832

3. U.S. Environmental Protection Agency. 2022 (updated). "Emissions & Generation Resource Integrated Database (eGRID)." https://www.epa.gov/egrid.

4. Zhou, Yan, David Gohlke, Luke Rush, Jarod Kelly, and Qiang Dai. 2021. *Lithium-Ion Battery Supply Chain for E-Drive Vehicles in the United States: 2010–2020*. Argonne National Laboratory, Report ANL/ESD-21/3. https://www.osti.gov/biblio/1778934.

Acknowledgements

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II Vehicle Modeling and Simulation

II.1 Electric Vehicle–Grid Analysis Modeling (Lawrence Berkeley National Laboratory)

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Project Funding (FY22): $250,000	DOE share: $250,000	Non-DOE share: $0
Project Funding (FY20-FY22): $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 conventional vehicles [3]. This is especially true in the freight industry in regard to heavy-duty (HD) 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 such vehicles could soon become a significant part of the transportation system, dramatically disrupting conventional modes of mobility in the process [6].

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 the smooth operation of the electric grid. Truck electrification will have far-reaching impacts on the environment in the form of greenhouse gas (GHG) emissions and air pollution. As such, this project has aimed to assess the benefits of HD truck electrification and emerging vehicle electrification opportunities in micro-mobility markets using the Grid-Integrated Electric Mobility (GEM) model. This national model simultaneously optimizes the provision and operation of shared heavy-duty automated and electric vehicles (SHAEVs) to provide electrified goods mobility alongside an economic dispatch of power generation [7].

Increasing levels of renewable energy are being added to the electric grid [8] while vehicle electrification is on the rise [9]. The potential impacts of integrating these technologies require new analytical methodologies that couple capabilities across the transportation and power sectors. This project has further extended 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. The EV charging schedule is planned based power system costs and power resources are dispatched to serve the charging demand.

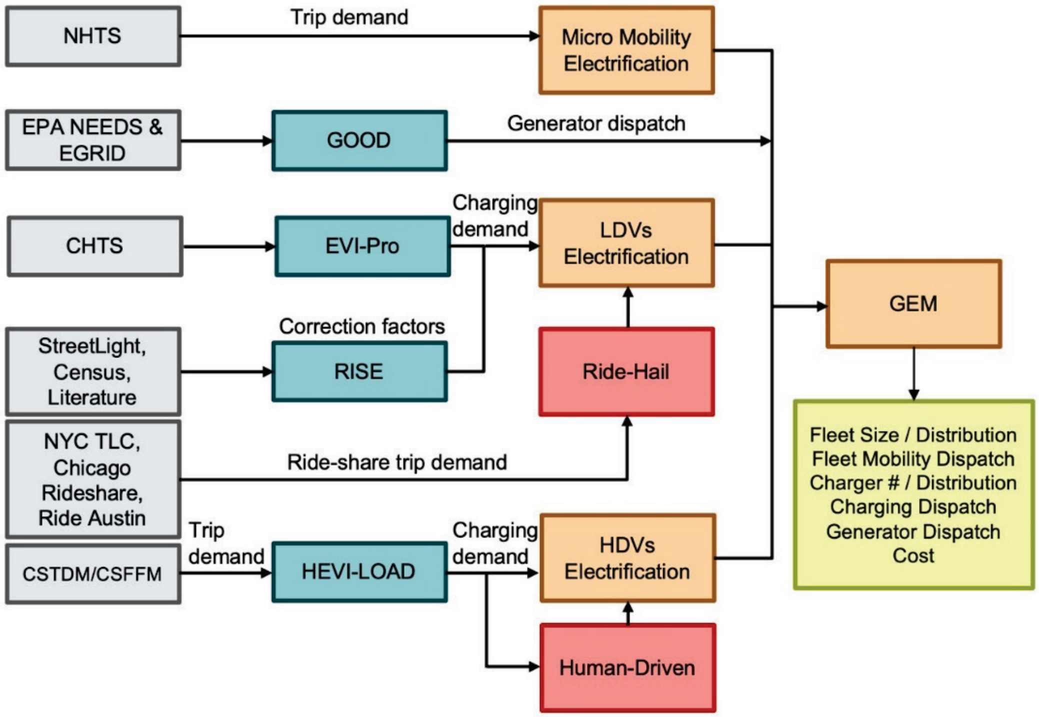
Objectives

The objective of this project is to leverage the existing GEM model and develop new methodological capabilities that enable the simulation of future electrified and automated freight fleets, human-driven electrified heavy-duty vehicles (HDVs), electric ride-hailing fleets, and micro-mobility, as well as 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 both unmanaged and smart charging scenarios, fleet size, 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 GHG emissions of the vehicle–grid systems.

Approach

The project developed an optimization model that solves the cost-minimizing dispatch of privately-owned and shared HDVs for operation and charging, the allocation of SHAEVs to serve goods delivery, the investment and construction of a 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 (GOOD) electricity model [10]. 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 following constraints: that mobility demand is always served, that energy is always conserved, and that generation assets on the grid are dispatched in merit order. Shared automated 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 market 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 is incorporated into the formulation for both SHAEVs and micro-mobility.

The scope of the GEM model is the contiguous United States, 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. The overall workflow of the expanded GEM is summarized in Figure II.1.1. The gray boxes are the input data source of each model. We used the National Household Travel Survey (NHTS), the California Household Travel Survey (CHTS), California Statewide Travel Demand Model/California Statewide Freight Forecasting Model (CSTDM/CSFFM) and Rideshare datasets to identify the trip demand of different mobility sectors. For power system data generation, we used two databases from the U.S. Environmental Protection Agency: National Electric Energy Data System (NEEDS) and Emissions & Generation Resource Integrated Database (eGRID). StreetLight, Census, and other literature review datasets were used as inputs to the Routing and Infrastructure for Shared Electric vehicles (RISE) model. The blue boxes in Figure II.1.1 are the modules used in the GEM framework. The Electric Vehicle Infrastructure – Projection (EVI-Pro) tool generates charging demand for light-duty vehicles (LDVs). For HDVs, the simulation components are developed using the Medium- and Heavy-Duty Electric Vehicle Infrastructure – Load Operations and Deployment (HEVI-LOAD). The RISE model to generate national-scale correction factors, and the power sector was included by coupling GEM to the GOOD electricity model. The orange boxes are the mobility sectors. In this expanded GEM framework, we considered multiple mobility groups such as LDVs/HDVs, the micro-mobility sector, human-driving LDVs/HDVs, and ridesharing for LDVs. The red boxes are the human-driven sub-categories in each mobility sector. The yellow box is the expected output from the GEM framework.



NYC TLC = New York City Taxi and Limousine Commission

Figure II.1.1 Expanded GEM model processing workflow. Source: Lawrence Berkeley National Laboratory

Results

Figure II.1.2 shows the overall charging load profile for a variety of scenarios of electrification and automation in the heavy-duty sector with the use of different levels of charging power and different charging behaviors (human charging assignments: come and charge, automated charging assumption: optimal charging time schedule to reduce energy cost and load peaks). We assume for all the electrified trucks, *S* of them are SHAEVs (*S* = 1, 25, 50, 75, 99%), and *1-S* of them are human-driven fleets (*P* = *1-S*). Among the human-driven fleets, 50% of the fleets use smart charging assignments, and the other 50% of the fleets simply charge when arriving at their destinations. As the penetration of the SHAEV fleet increases, the overall charging load profile shows a smoother fluctuation. The peak daily charging load reduces by 47% as the penetration of SHAEVs increases from 1% to 99%. This reduction in fluctuation and peak load is due to the sophisticated job assignment and charging assignment assumptions for SHAEVs. Moreover, for the human-driven electric HDV fleets, the smart charging assignment fleet shows a lower charging demand in peak energy usage hours (peak energy usage is assumed to occur from 5 PM to 10 PM). The human charging assignment (arrive and charge), on the other hand, is more likely to charge during those times and unlikely to charge during non-peak hours.

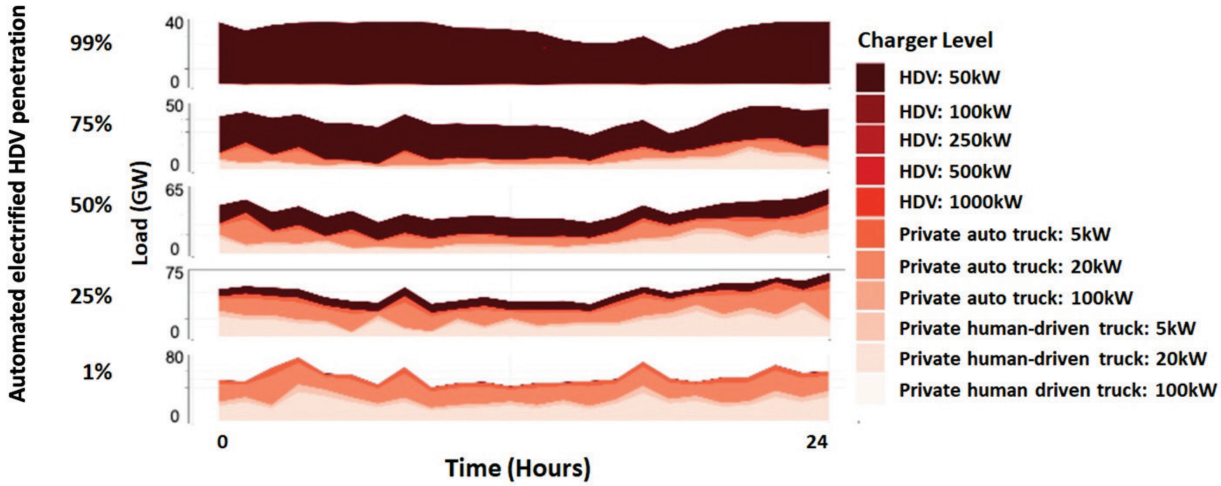


Figure II.1.2 Electrified HDV daily charging load profiles across scenarios of electric and automated vehicle (EV/AV) penetration. Source: Lawrence Berkeley National Laboratory

Number of chargers. Figure II.1.3(a) shows the number of chargers needed. As with fleet size, there are far more chargers when SHAEVs are low (S = 1%) than in a counterfactual scenario of high SHAEV penetration (S = 99%), reflecting much higher utilization among SHAEV chargers. When the SHAEV penetration increased from 1% to 99%, the overall number of chargers dropped from 396 million to 242 million, resulting in a reduction of 38%. This reduction is primarily due to the reduction of human-driven electric HDV fleet-related chargers, as those chargers have a lower sharing factor than SHAEV-related chargers.

Peak load. Figure II.1.3(b) shows the grid peak load, which also decreases substantially as the fraction of mobility demand met by SHAEVs increase peak demand is 159 GW at S = 1% and 135 GW when S = 99%. These results indicate that the overall peak load will decline as the increment of SHAEV fleet size increases. However, the peak load for individual fleet components may vary with different SHAEV penetration. This is a result of the joint optimization of the charging demand of all mobility sectors. The relaxation of high truck charging demand during peak hours may encourage charging for other fleet components in the electric mobility system to result in an overall minimum operational cost.

Fleet size. Figure II.1.3(c) shows the optimal fleet size of all types of vehicles in GEM modeling. This study focuses on the SHAEVs and human-driven electrified HDVs. Modeling shows that 47 million total electric vehicles are eliminated as S increases from 1% to 99%. This reduction in fleet size is primarily due to the higher utilization of job assignments for the SHAEVs. With the relaxation of human-driven constraints, SHAEVs are likely to complete more jobs per day than human-driven electric HDVs.

Total costs. Figure II.1.3(d) shows the overall cost changes as the fraction of SHAEVs increases. The fleet and infrastructure costs for human-driven electrified HDVs decrease on a larger scale compared to the incremental changes in fleet and infrastructure costs related to the increase of SHAEV fleets. The overall cost related to mobility electrification decreased from $1,085 billion to $889 billion with the penetration of SHAEVs increasing from 1% to 99%, resulting in a reduction of overall cost by 18%. The reduction in overall cost is a joint result of charging infrastructure reduction, peak load reduction, and fleet size reduction, which reduces the infrastructure cost, power system operation cost, and fleet cost, respectively.

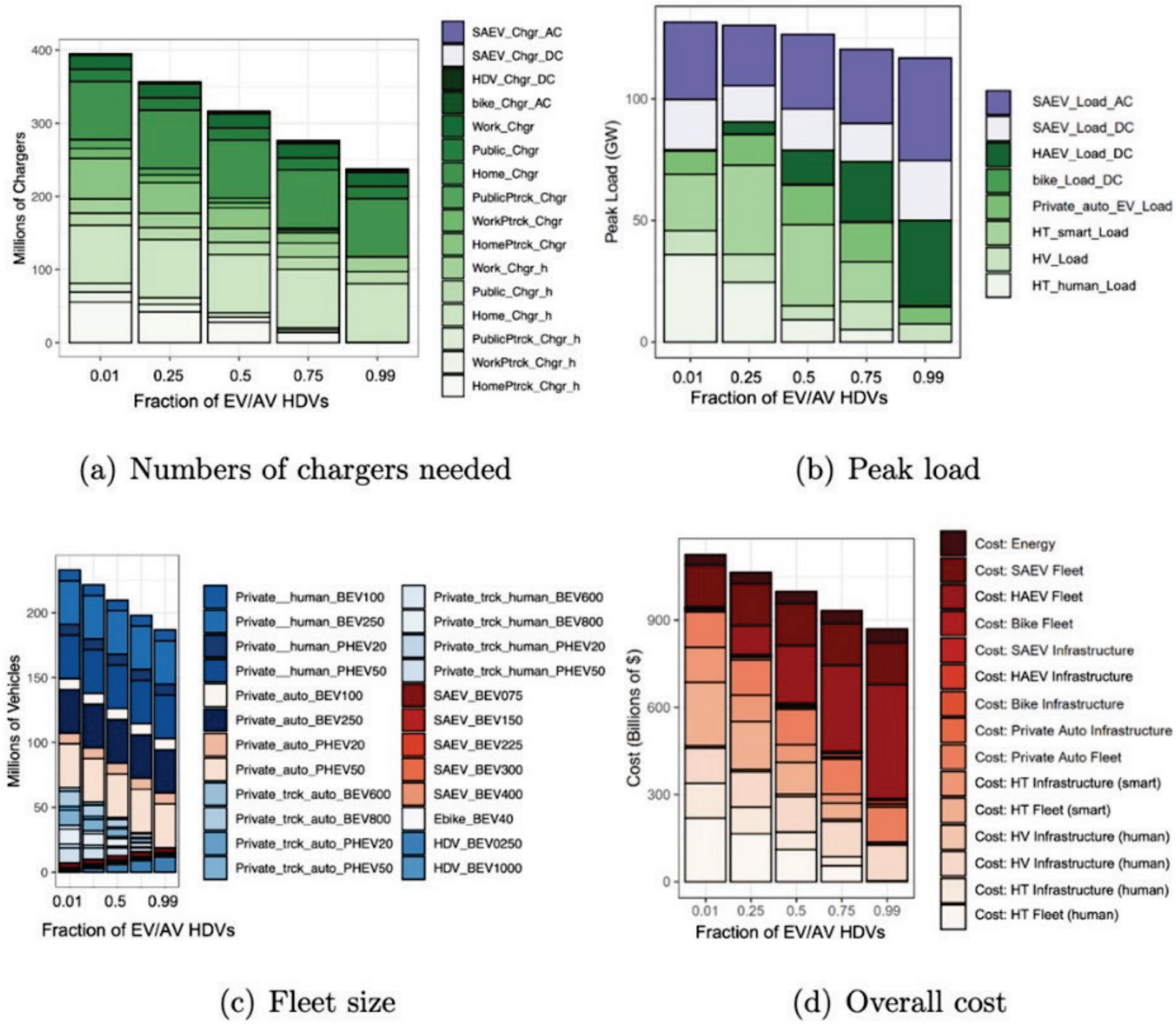


Figure II.1.3 GEM system-level outputs across scenarios of automation and electrification for HDVs: (a) number of chargers, (b) peak load, (c) fleet size, and (d) overall cost. Source: Lawrence Berkeley National Laboratory

Figure II.1.4 shows results for key outputs from the electrification of micro-mobility (i.e., e-bike) scenarios in the GEM model averaged over time (i.e., the selection of days that were simulated) and geography, displayed across the full range of the fraction of passenger demand satisfied by bike-to-car trip shares. The results demonstrate that, as e-bikes replace LDVs for short-distance trips and the share of bike trips increases, there are decreases in overall peak power demand, overall operational cost, fleet size, and GHG emissions.

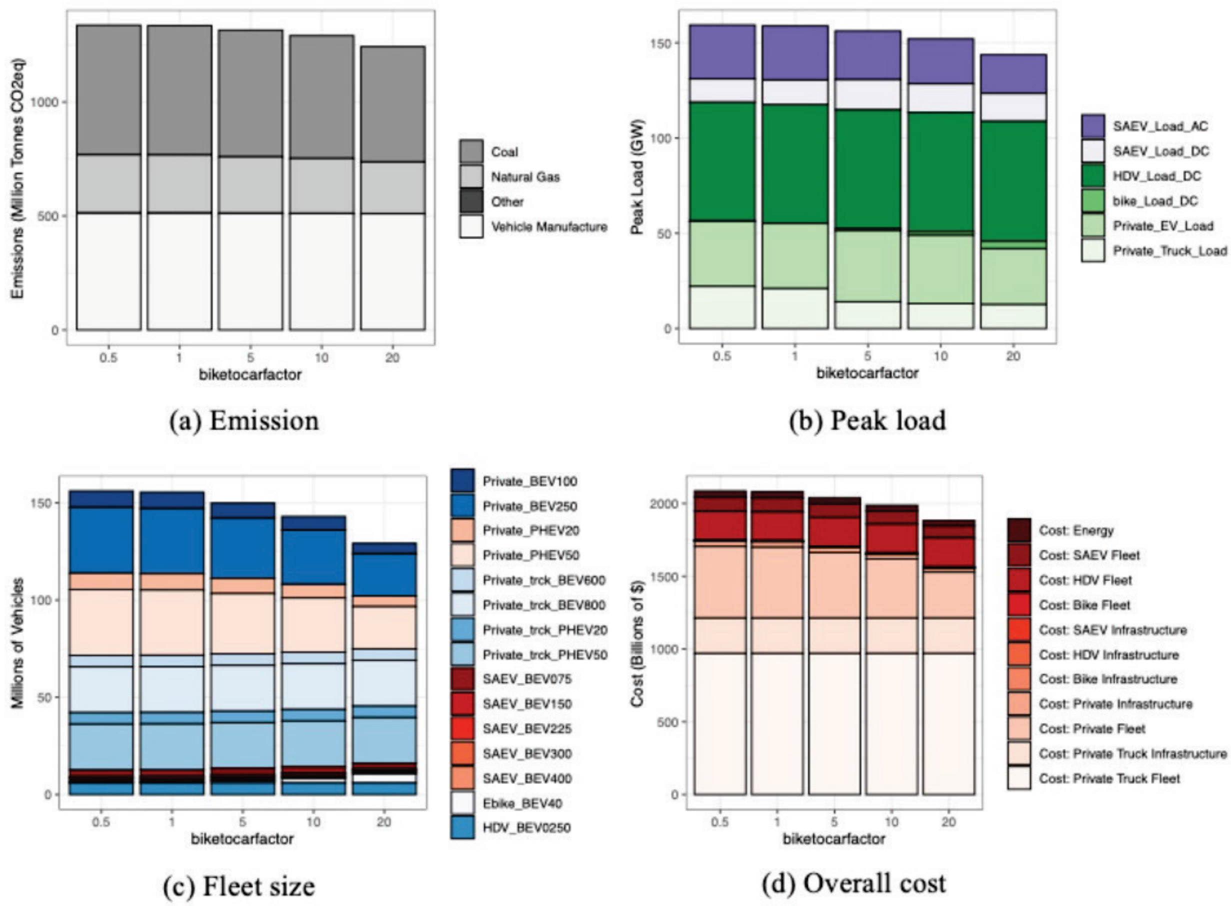


Figure II.1.4 Penetration of electrified micro-mobility panel showing increases in the fraction of bike-to-car trips and associated changes in (a) GHG emissions, (b) peak power demand, (c) fleet sizes, and (d) overall costs. Source: Lawrence Berkeley National Laboratory

Conclusions

The configuration of the freight system in which SHAEVs serve goods delivery has substantial benefits over a system that relies on privately-owned electrified trucks or gasoline-powered vehicles. Overall, project results suggest that freight automation reduces total costs by increasing operating efficiency, leading to faster goods delivery within the transportation system. Lower GHG emissions would be an additional benefit. 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 optimization model (GEM).

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

The above-mentioned findings are of notable significance, as they may act as a beacon of direction for private fleet operators in their strategic acquisition of electrified fleet components. This work shall also proffer advice to policy makers and transportation planners regarding their forthcoming freight electrification and infrastructure plans.

Key Publications

1. Hong, Wanshi, Alan Jenn, and Bin Wang. 2023. "Electrified Automated Freight Benefit Analysis on Fleet, Infrastructure and Grid Leveraging Grid-Electrified Mobility (GEM) Model." *Applied Energy*. 335: 120760. https://www.sciencedirect.com/science/article/abs/pii/S0306261923001241

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The authors of this work are Bin Wang, Srinath Ravulaparthy, Wanshi Hong, Fan Tong, Alan Jenn, and Cong Zhang. The work described was sponsored by the U.S. Department of Energy (DOE) Vehicle Technologies Office under the Analysis Program. The following DOE Office of Energy Efficiency and Renewable Energy managers played essential roles in establishing the project concept, advancing implementation, and providing ongoing guidance: Raphael Isaac, Rachael Nealer, Jake Ward, 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.

II.2 Light-Duty Vehicle Choice Modeling and Transportation Decarbonization Analysis (National Renewable Energy Laboratory)

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U.S. Department of Energy
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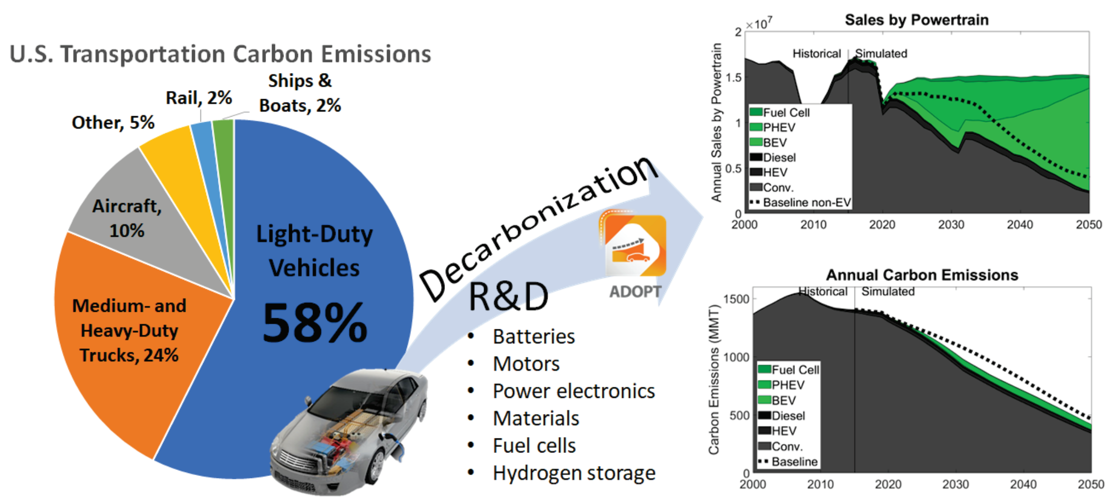
Start Date: October 1, 2021 End Date: September 30, 2022
Project Funding (Previous): $600,000 DOE share: $600,000 Non-DOE share: $0
Project Funding (FY22): $300,000 DOE share: $300,000 Non-DOE share: $0
Total Project Funding: $900,000 DOE share: $900,000 Non-DOE share: $0

Project Introduction

The U.S. Department of Energy's (DOE's) goal is to deliver a clean energy future. This project estimates the decarbonization impacts on light-duty vehicles from research and development work supported by DOE's Vehicle Technologies Office (VTO) and Hydrogen and Fuel Cell Technologies Office (HFTO). The project uses a validated consumer choice model to estimate vehicle sales, energy consumption, and carbon emissions for technology improvements under different market conditions. Various scenarios were simulated to find pathways to decarbonization.

Objectives

The objective is to estimate the impact of DOE-supported research and development on the decarbonization of light-duty vehicles. Transportation is the biggest contributor to carbon emissions, and light-duty vehicles produce most of those emissions. [1], as shown in Figure II.2.1.

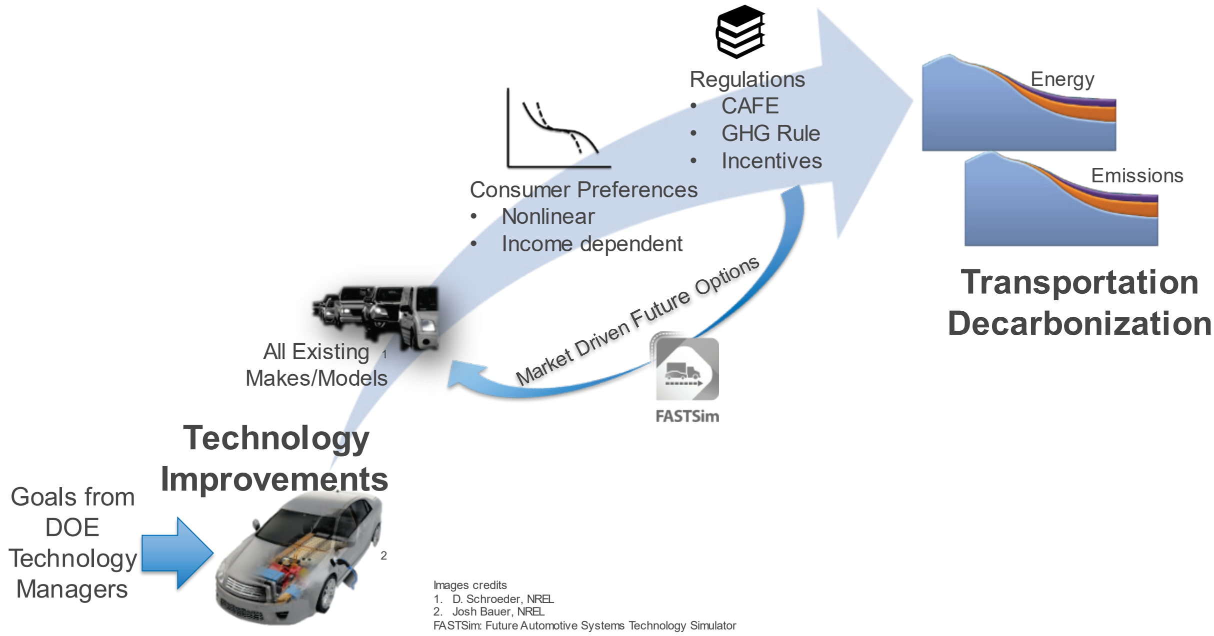


EV = electric vehicle; BEV = battery electric vehicle; HEV = hybrid electric vehicle; PHEV = plug-in hybrid electric vehicle; R&D = research and development

Figure II.2.1 Decarbonization pathways. Source: National Renewable Energy Laboratory

Approach

The project used the Automotive Deployment Options Projection Tool (ADOPT) to estimate the impact of DOE-supported research and development on sales, energy consumption, and carbon emissions to find pathways to decarbonization. ADOPT has been downloaded almost 1,000 times by industry, government organizations, research institutions, and universities. As summarized in Figure II.2.2, ADOPT includes the key elements and methodology that enable the model's outputs to match historical sales—providing confidence in the results.



GHG = greenhouse gas; CAFE = Corporate Average Fuel Economy

Figure II.2.2 ADOPT's approach to finding decarbonization pathways. Source: National Renewable Energy Laboratory

Simulations start with the over 700 existing vehicle makes, models, and options. This provides realism, captures any outlier characteristics of the best-selling advanced vehicles, and allows regulatory influences to be modeled. Sales among the vehicles are estimated based on their attributes, including price, fuel cost per mile, acceleration, size, and range. The modeled consumer value of the attributes changes nonlinearly across their range and as a function of consumer income. For example, differences in acceleration are more important for very quickly or very slowly accelerating vehicles, and acceleration importance increases for high-income households. This approach enables ADOPT to match historical sales in many dimensions [2], [3] and across multiple years—all of which help to provide confidence in the results. The consumer preferences are also used to create new future vehicle options based on market conditions using the integrated Future Automotive Systems Technology Simulator (FASTSim) vehicle powertrain model (which has been downloaded more than 6,000 times) [4]. Using an optimization routine, ADOPT sends FASTSim different component sizes, such as engine or battery size, and gets back vehicle attributes, including efficiency and acceleration. ADOPT then uses those attributes to estimate sales and find the best component sizes. This leads to market-driven vehicle options. For example, as battery prices decrease, ADOPT tends to create BEVs with larger batteries that provide longer range and better acceleration. The sales estimates feed into a stock model that tracks sales, miles traveled, and survival of vehicles to quantify energy consumption and carbon emissions.

Key Assumptions

The project used assumptions from VTO and HFTO that reflect technology improvement goals for all major powertrain components [3]. Some key assumptions include the battery price reductions, fuel prices, and fuel carbon intensities, each of which is shown in Figure II.2.3. Battery prices go down to $90/kWh by 2050. The price of electricity is assumed to remain relatively flat while grid generation becomes clean (i.e., zero-emissions) by 2035.

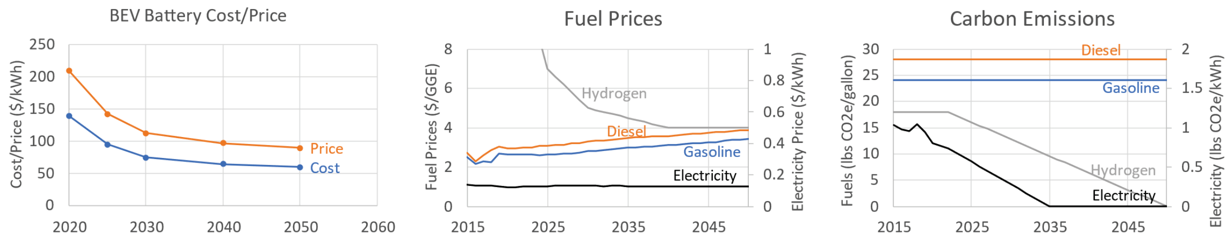


Figure II.2.3 Key assumptions for battery cost, fuel prices, and carbon emissions. Sources: DOE VTO, DOE HFTO, and EIA [5]

Results

ADOPT's results suggest that the technology improvements, without any changes in regulations or incentives (before the Inflation Reduction Act was passed), were not enough to meet the 50% clean vehicle sales goals by 2030, as shown in Figure II.2.4. The technology improvements, which assume contributions from VTO and HFTO research, had a significant impact on clean vehicle sales—but not as early as has been targeted.

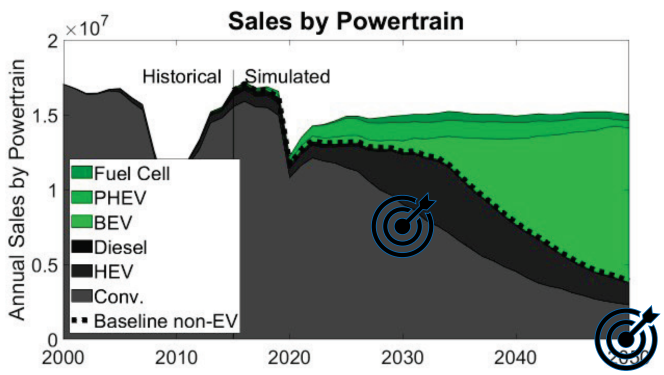


Figure II.2.4 Sales by powertrain without changes in regulations or incentives (before the Inflation Reduction Act). Source: National Renewable Energy Laboratory

Missing the target for clean vehicle sales shares led also to missing the 2050 carbon reduction goal, as shown in Figure II.2.5.

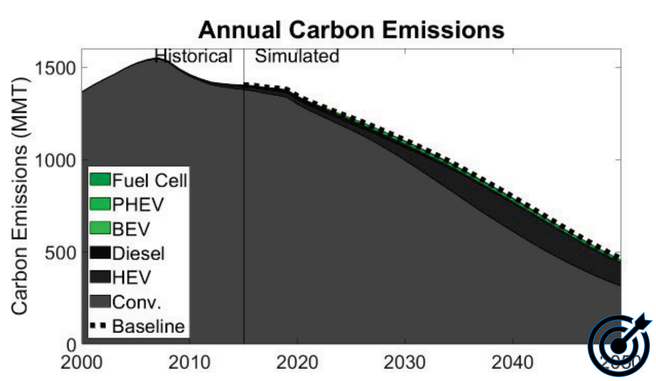


Figure II.2.5 Annual carbon emissions without changes in regulations or incentives (before the Inflation Reduction Act). Source: National Renewable Energy Laboratory

ADOPT estimated that the technology improvements with additional regulations and incentives from the Inflation Reduction Act were enough to meet the 2030 clean vehicle sales goal and improve the 2050 outcome, as shown in Figure II.2.6.

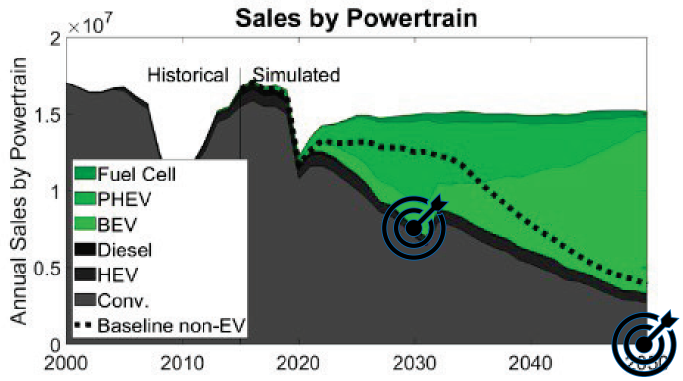


Figure II.2.6 Sales by powertrain with additional regulations and incentives. Source: National Renewable Energy Laboratory

Many other scenarios were run to find sensitivities to technology improvement progress and market conditions, as shown in Figure II.2.7.

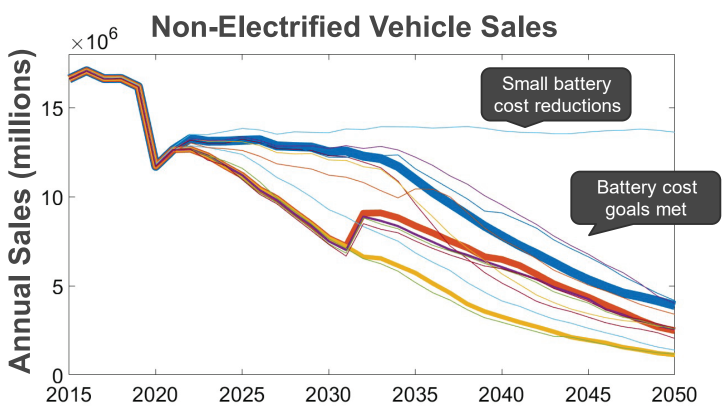


Figure II.2.7 Non-electric vehicle sales assuming different technology and market conditions. Source: National Renewable Energy Laboratory

For most scenarios, technology improvements, with contributions from VTO and HFTO research, led to mostly clean vehicle sales by 2050. The addition of incentives and regulations increased early clean vehicles sales. Without battery cost reductions, clean vehicle sales remained flat.

Conclusions

Transportation is responsible for most carbon emissions. Within transportation, light-duty vehicles are the biggest contributor. Technology improvements, including contributions from VTO and HFTO, along with supporting market conditions, are essential for meeting the clean vehicle sales goals and resulting carbon emission goals.

Key Publications

1. Brooker, Aaron, Alicia Birky, Evan Reznicek, Jeff Gonder, Chad Hunter, Jason Lustbader, Chen Zhang, Lauren Sittler, Arthur Yip, Fan Yang, and Dong-Yeon Lee. 2021. *Vehicle Technologies and Hydrogen and Fuel Cell Technologies Research and Development Programs Benefits Assessment*

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II.3 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: March 31, 2023
Project Funding (FY22): $142,505 DOE share: $127,383 Non-DOE share: $15,122
Project Funding (Total): $441,028 DOE share: $396,089 Non-DOE share: $44,939

Project Introduction

This project will analyze heavy-duty freight movement and will estimate the transmission and distribution impacts of electrification of these vehicles. Currently Class 7 and 8 electric tractor trucks are available in early production forms, with larger quantities 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 what the potential difficulty and cost will be for installing infrastructure to recharge these vehicles, which may require "slow" charging solutions (up to 20–100 kW per plug for overnight charging) or "fast" charging solutions (potentially 1+MW 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 necessitate significant service expansion and upgrades to electricity distribution systems.

Objectives

The goal 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 and utilities to society overall. This goal will be accomplished by leveraging cutting-edge electrification and grid analytics to demonstrate new techniques to characterize electrification needs, to align the needs with the existing grid capacity, to assess various electrification solution options where capacity is not available, and to 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. This is a critical first step toward 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.

The two tasks, Task 4 and 5, in this budget period are defined to assess integration solutions for heavy-duty vehicle electrification. Specifically, integration solutions can either reduce or mitigate grid impacts. This nuance is reflected in the two tasks.

The objective of Task 4 Grid Reinforcement and Cost Assessment is to identify grid reinforcements to enable the electrification of vehicle fleets. This includes considering both traditional mitigation solutions (e.g., reconductoring, load transfers, and voltage regulations) and non-wire alternatives (e.g., energy storage systems, demand response, and photovoltaic systems).

The objective of Task 5, Charge Profile Modification Evaluation, is to assess how the demand profile created by fleet electrification could be modified to reduce impacts on the grid. This can be achieved either via charge management or via behind-the-meter distributed energy resources that the fleet manager would manage.

Approach

Task 4: Grid Reinforcement and Cost Assessment

The first and foremost step is to assess the severity of the grid impacts from the new electrification load, including thermal loading and voltage conditions. The type of integration solution will depend on the operational constraint that the feeder is experiencing, and the severity of the impact will be highly dependent on the location where the load will manifest itself and the characteristics of the feeder itself. The second step is to identify feasible grid infrastructure solutions that would enable the integration of the new demand. Finally, the third step is to identify the most cost-effective solution by evaluating each feasible solution for its cost and the benefit provided to the system.

Task 5: Charge Profile Modification Evaluation

Unlike traditional loads (residential, commercial, etc.), electric vehicles (EVs) provide an inherent flexibility in terms of when the load manifests within the system. It is common for vehicles to be parked over extended periods of time (e.g., overnight) when they would be able to recharge. Vehicles could charge as soon as they come back to the depot, or a fleet could have a strategy to minimize peak power demand, among other charging strategies as illustrated in Figure II.3.1. The approach taken in this study is to assess different charging strategies and compare them to temporal grid constraints to better understand each strategy's effectiveness in reducing grid impacts. Secondly, behind-the-meter distributed energy resources solutions are also evaluated for scenarios in which charge management does not provide a feasible solution.

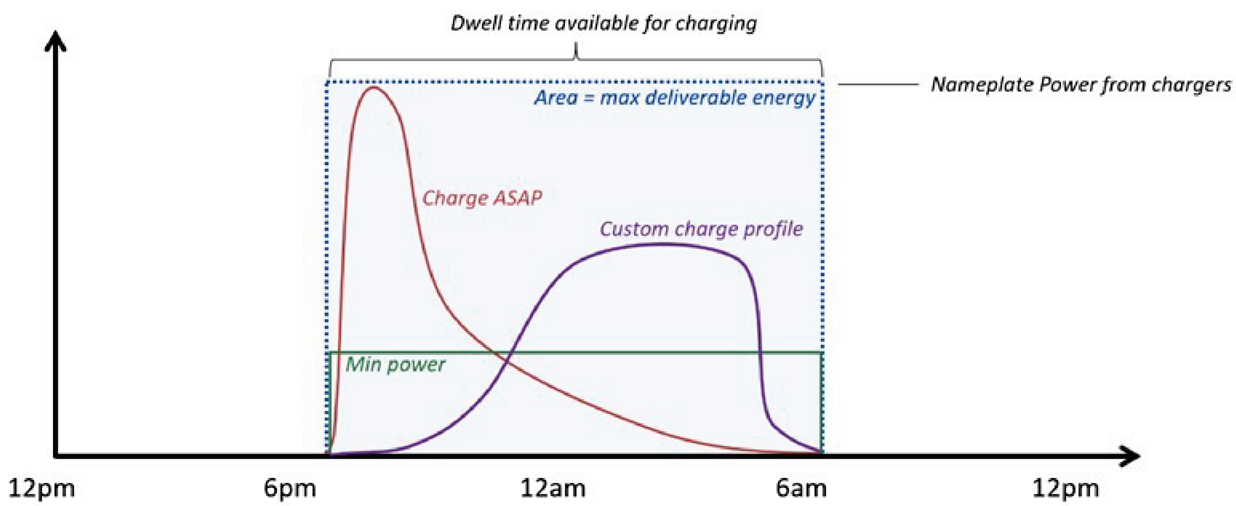

Figure II.3.1 Illustrative example of different charging profiles (charging as soon as possible, charging while minimizing peak power, using a custom charging profile, etc.). Source: EPRI

Results

Task 4: Grid Reinforcement and Cost Assessment

For the purposes of this study, a location for the fleet depot and EV load shapes are assumed, as shown in Figure II.3.2(a), (b), where the hosting capacity at that location is 3.1 MW during peak load conditions, as shown in Figure II.3.2(c). Conventionally, the industry has focused on assessing grid capacity during peak load conditions because such conditions are the most limiting. However, because of the specific temporal characteristics of EV charging demand, the project team performed an 8,760-hour time-series hosting capacity analysis, using grid data to model the temporal behavior of the existing loads. An hourly box plot shown in Figure II.3.2(c) shows the range of hosting capacity results for each hour of the day, with the blue dotted line showing the most limiting values for that specific hour. Note that the lowest hosting capacity occurred at 2 PM but that there is significant additional capacity (~7 MW) during overnight hours, even during the worst day of the year.

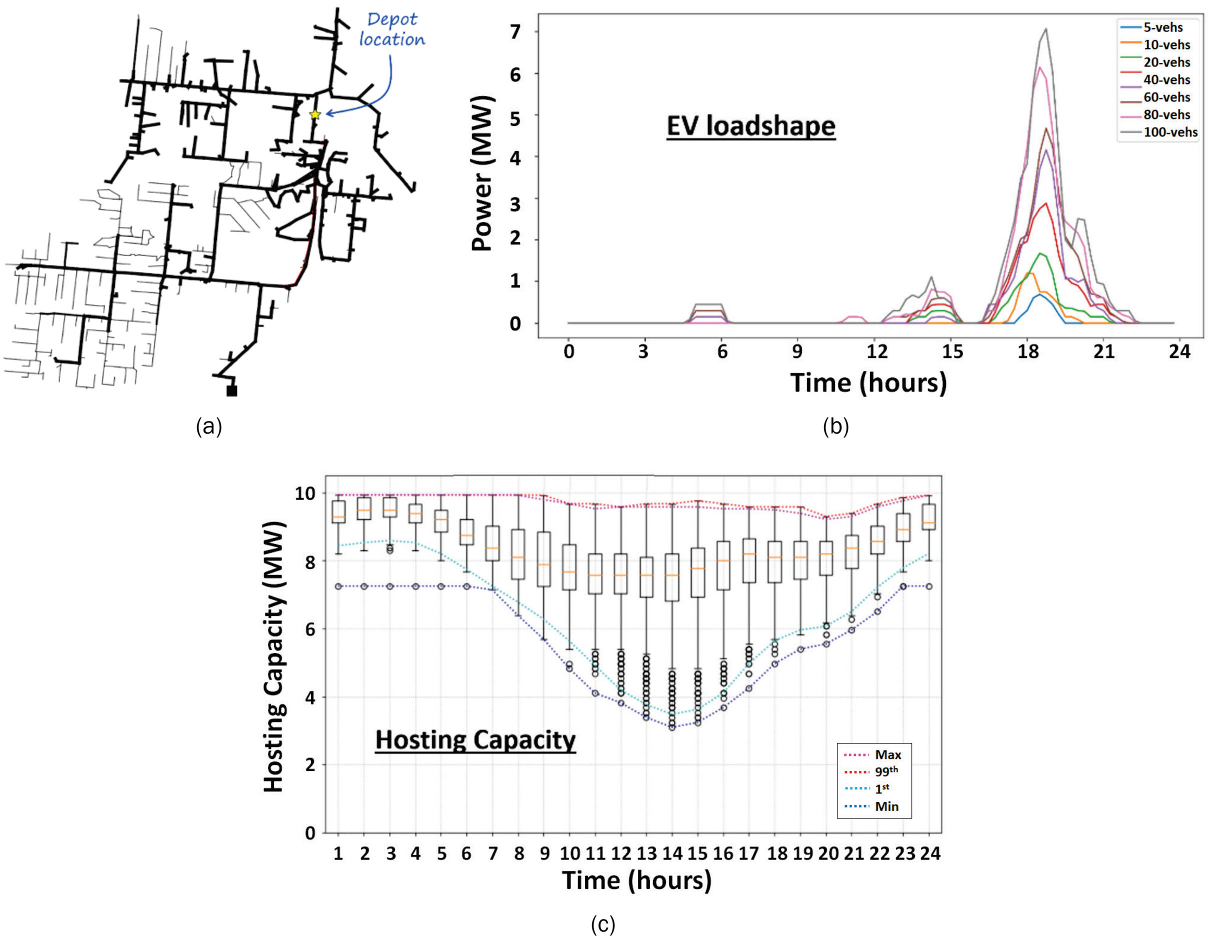

Figure II.3.2 Scenario definition highlighting (a) the assumed depot location, (b) the EV load shapes, and (c) the time-series hosting capacity at that location. Source: EPRI

As mentioned in the approach, the first step is to identify the grid constraint and its severity, using this information to identify the type of integration solutions to consider. In this scenario, the main constraint on the feeder is a thermal constraint between the location of the depot and the feeder head, caused by the amount of load downstream of the depot, as well as the feeder characteristics, with some conductors having limited capacity. Hence, the project team considered a few different integration solutions, including reconductoring, load transfers, and utility-owned energy storage, as illustrated in Figure II.3.3(a), (b), and (c), respectively. The purpose of reconductoring is to identify distribution lines to upgrade that would otherwise experience an overload. The load transfers approach considers tie-points with neighboring feeders to transfer sections of the feeder to another distribution feeder to relieve the thermal constraint. Lastly, grid-side energy storage relies on the concept that peak load conditions (and thus the thermal constraint) occur only a few hours of the year and that the energy storage system could discharge to relieve the constraint for its duration.

Depending on a number of factors, the grid infrastructure necessary for integrating the new load will vary drastically. Hence, it is important to note that integration solutions will be specific to the scenario. The feeder characteristics will affect the length of reconductoring, the number or location of tie points with neighboring feeders will dictate the feasibility of load transfers, and the demand profile compared to existing load on the feeder will affect the power and energy characteristics of the energy storage. Figure II.3.3(a) shows the section of line that needs to be reconductored (0.7 miles, in this case), Figure II.3.3(b) shows the three tie-points with neighboring feeders (tie point 3 is the only feasible option in this example), and Figure II.3.3(c) indicates the power and energy needed from the storage system (1.35 MW, 0.68 MWh in this scenario).

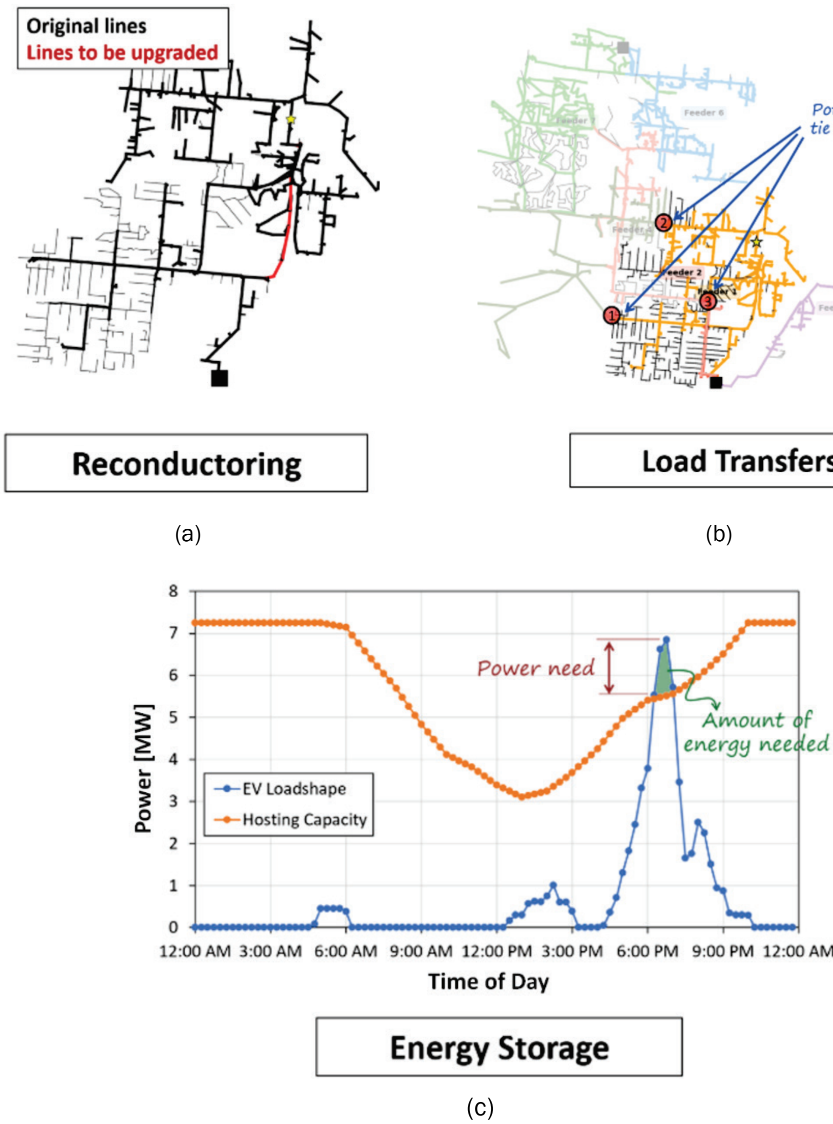

Figure II.3.3 Mitigation solutions to accommodate fleet electrification on distribution feeders for (a) reconductoring, (b) load transfers, and (c) energy storage. Source: EPRI

Task 5: Charge Profile Modification Evaluation

The other type of integration solution is to reduce grid impacts in lieu of mitigating them. Specifically, EV charge management provides significant flexibility in the timeline and severity of the load impact. In this project, five charging strategies are explored to assess whether charge management could be used to electrify a fleet without the need for additional grid investments. Charging as soon as possible ("immediate") is considered as the default strategy since it does not require any management. In contrast, charging as late as possible ("delayed") is defined as having each vehicle start charging at the latest possible time that allows for the vehicle to be fully charged in time for its scheduled departure. Two variations of these charging strategies were also considered; the size of the chargers is varied to show the impacts on the load shape: "correct" (perfectly matched to need) and "over-sized." Finally, the analysis also considers a charging strategy that minimizes power needs out of the depot ("min_power"). The resulting charging profiles are plotted in Figure II.3.4.

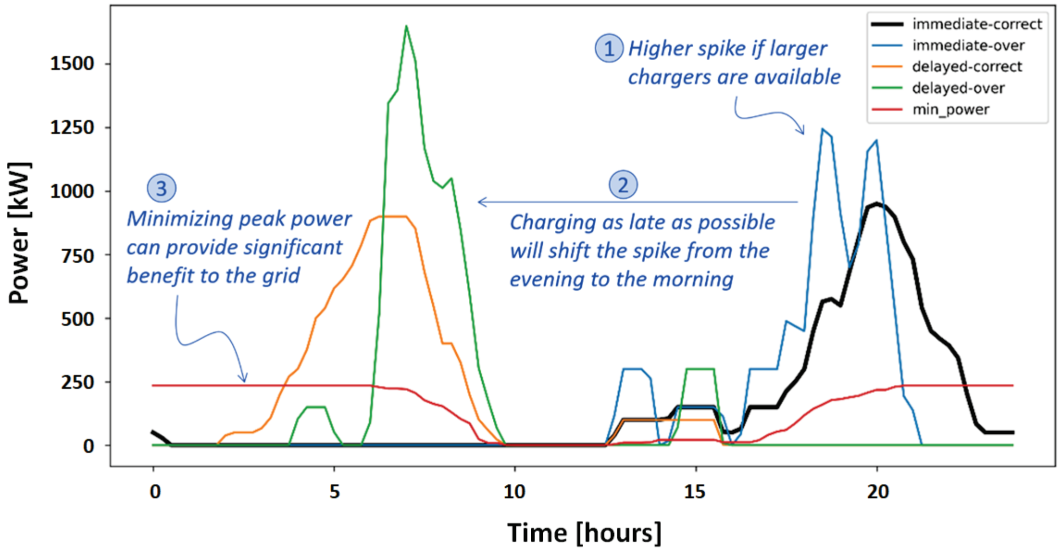

Figure II.3.4 Load profile under different charging strategies. Source: EPRI

Note how high-power chargers will shorten the duration of the curve but increase the peak since vehicles can charge at power levels that exceed their requirements. Delayed charging will shift the peak to the morning hours instead of evening hours. Whether this solution is feasible will depend greatly on the vehicle schedule, which will vary from sector to sector. Lastly, it is possible to drastically reduce the power need from a depot if the vehicles charge at a lower power level throughout their dwell period at the depot. This is especially important since it can reduce the impact on the grid.

Another concept derived from this work is that hosting capacity in terms of power may provide only one perspective on the capacity of distribution feeders to accommodate fleet electrification, especially considering that there may be additional capacity overnight. A new metric for distribution engineers to consider is energy availability. Energy availability is defined as the additional energy available over a period of time considering the system capacity and existing demand. The units could be in either megawatt-hours per day or terawatt-hours per year, depending on the timescale. This metric quantifies the energy availability on a distribution feeder (fleet electrification needs are often quantified as an energy requirement in megawatt-hours since the load profile has some inherent flexibility), allowing distribution engineers to nuance hosting capacity results and better assess the electrification opportunity of a system. Figure II.3.5 provides a heatmap of the energy availability at different locations on a distribution feeder under two charging strategies. Unconstrained charging refers to the total energy available in one day if the fleet could charge up to the hosting capacity. In the earlier scenario, this would be 3.1 MW for 24 hours, or 74.4 MWh. The constraint-based charging energy availability assumes charging up to the maximum power for each hour of the day. In this scenario, this resulted in 136 MWh, which shows additional available energy for fleet electrification if the charging strategy is coordinated with grid constraints.

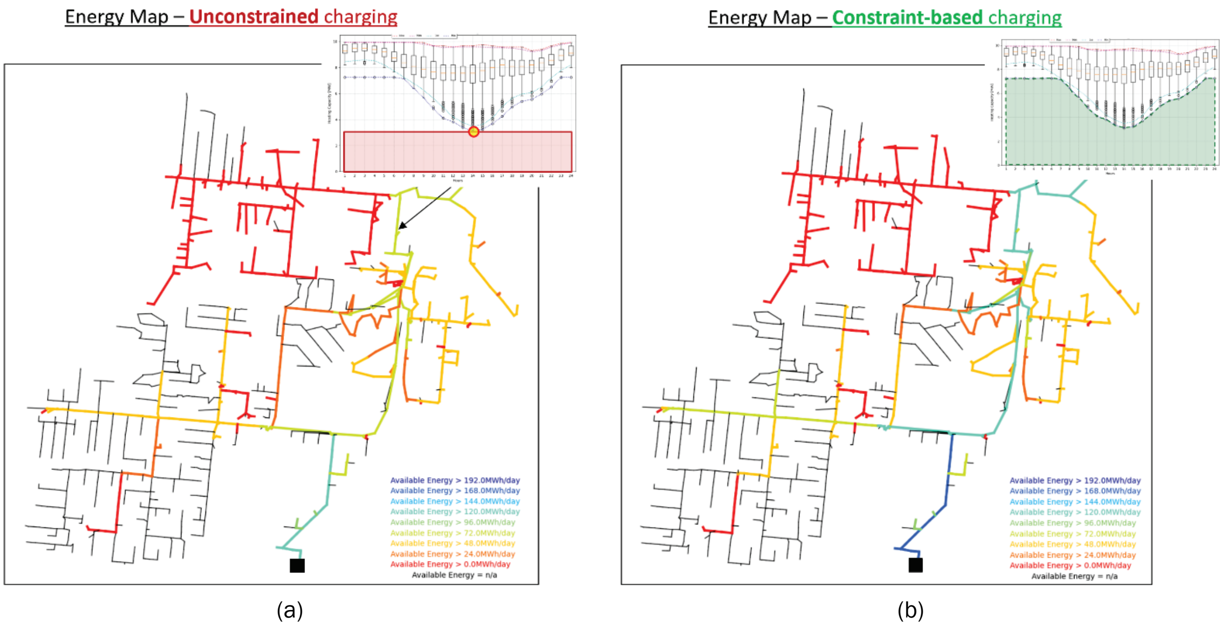

Figure II.3.5. Energy availability at different locations on a distribution feeder under two types of charging strategies: (a) unconstrained and (b) constraint-based. Source: EPRI

Conclusions

This project is ongoing, so there are no broad conclusions at this time. So far, the project has produced load shapes for heavy-duty charging in a variety of scenarios for depot and en-route charging (an FY 2021 accomplishment), transmission upgrade requirements for rural en-route charging (FY 2022 work, but not discussed in detail here), and distribution requirements for depot charging, as discussed above. As this work continues, these results will be finalized and described in a final report and workshop in FY 2023.

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II.4 Integrated Modeling and Technoeconomic Assessment of Electric Vehicle Community Charging Hubs (University of Illinois Urbana–Champaign)

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Project Funding (FY22): $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

Democratizing access to charging infrastructure is a prerequisite for equitable electric vehicle (EV) adoption and use. Residential EV charging is the most prevalent and convenient option. However, there are barriers to home chargers' installation and access [1], especially for residents of multi-unit dwellings (MUDs). Capital cost burden, renters' rights, and ineffective shared charging management hinder MUD charger deployment and ease of use. The charger access gap is larger at locations with a greater MUD share [2]. American Housing Survey data reveal disparities in garage availability (where home chargers could be installed) in MUDs compared to single-family residences [3]. When charging at home is not an option, EV owners will face higher charging expenses [4] and an increased probability of vehicles not meeting their desirable state of charge before the beginning of their day. This is a crucial charging equity problem that must be addressed.

We introduce the concept of community charging hubs, envisioning that MUD parking lots will host shared chargers while the residents' charging demand is centrally managed to account for their travel patterns and adhere to their schedule constraints. We formulate the shared charging schedule and management problem in MUDs as a job shop scheduling (JSP) problem. We propose a rule-based heuristic approach to solve the problem. This technique is transferable to various geographical locations and contexts and provides charging scheduling solutions in a computationally efficient manner. We define small, medium, and large charging hub configurations that meet the same level of charging demand; thus, stakeholders can select the level of service that they want a particular hub to offer as well as the levelized cost of charging that is aligned with their objectives. For each hub, we estimate its charging power profile. We demonstrate trade-offs between the community charging hub's performance and its levelized cost of charging for alternative station configurations in Chicago, Los Angeles, and New York City.

Objectives

Our project aims to use shared charging hub deployment and ease of managed use to directly address the barriers that hinder MUD residents' EV ownership. The model's objective is to minimize the system's makespan and the total system waiting time, aiming for high charging infrastructure utilization rates and positive charging experiences for MUD residents. The technoeconomic assessment supplements our analysis, estimating the levelized cost of charging for hub configurations with Level 2 and Direct Current Fast Charging (DCFC) stations, leveraging empirical data on capital and operational costs, electricity rates, and energy sold. This information can provide insights into the decision-making processes of a diverse set of entities engaged in MUD charger deployment and operations.

Approach

Charging Schedule Management

We modified the classical JSP for EV charging scheduling in MUDs. Two objectives are set in our study. The charging scheduling model cannot be promptly solved with commercial solvers, such as CPLEX and GUROBI [5]. Instead, we propose a heuristic method that consists of three modules shown in Figure II.4.1. In Module 1, charging sessions are assigned to chargers according to a set of assignment strategies. In Module 2, the sequences of charging sessions for each charger are based on the best of four dispatching rules, determined by a decision model. In Module 3, several charging sessions are exchanged to further reduce waiting time for the MUD EVs.

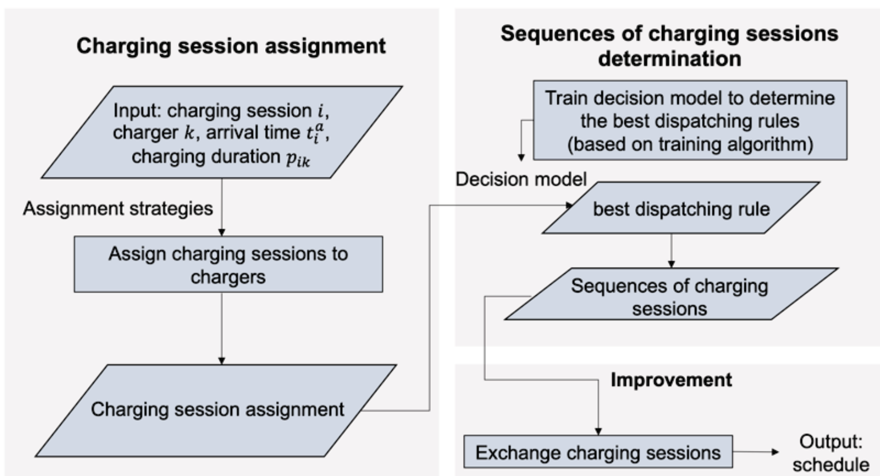

Figure II.4.1 A schema of the proposed heuristic method to solve the charging scheduling model. Source: University of Illinois Urbana–Champaign (UIUC)

Technoeconomic Assessment

The technoeconomic assessment evaluates the levelized cost of charging for nine scenarios. Each scenario involves one of three MUD locations—Chicago, Los Angeles, and New York City—and one of three charging hub ownership models—private company, utility, and residential. For each scenario, a 31-year discounted cash flow rate of return used inputs (converted to 2021 values [6], [7], [8]) to compute the levelized cost of charging such that a net present value of zero was achieved.

The applicability of the operating and electricity costs is dictated by the three ownership models, which determine who pays for the hub and how the hub is managed. A private company, such as a charger vendor or investor, is modeled to have a commercial electric load (separate from the MUD building), a 10% internal rate of return, and pay for data and network contracts. A utility owner, the existing utility company that services the area, is modeled to have a residential electric load, a 6% internal rate of return, and pay for data and network contracts. Lastly, a residential owner (group of residents or property owner) is modeled to have a residential electric load, a 3% internal rate of return, and no data or network contracts.

Numerical Experiments

We apply the modified JSP charge scheduling model and technoeconomic assessment in Chicago, New York City, and Los Angeles MUDs for numerous charger compositions. For each metropolis, a scenario is created where EV drivers compete for a limited number of chargers in one MUD. Figure II.4.2 displays average metrics for MUD size, number of residents per building, number of EVs per building, and feasible intervals (bars) of Level 2 and DCFC ports in each scenario.

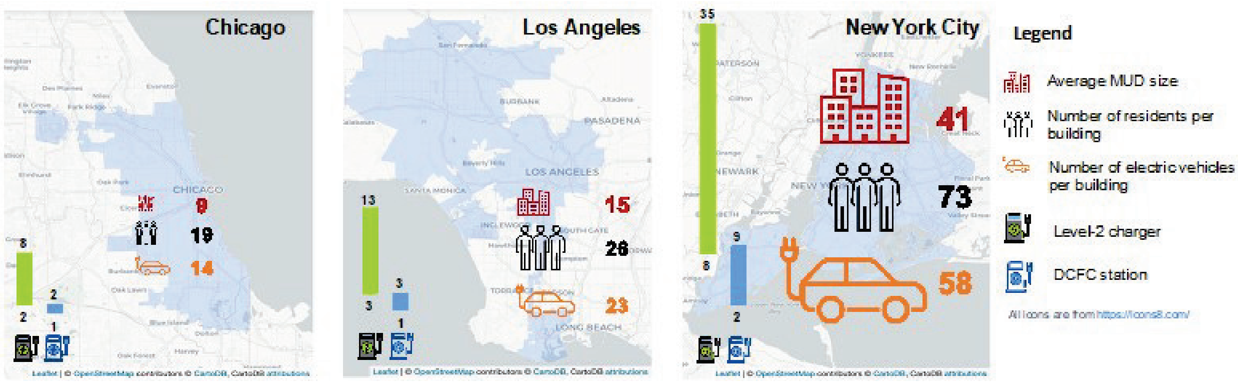

Figure II.4.2 Average MUD characteristics in Chicago, Los Angeles, and New York City. Source: UIUC

Results

Coupled Charging Hub Performance and Levelized Cost of Charging

We demonstrate the hub's trade-offs between total waiting time and the levelized cost of charging. These trade-offs are shown for 46 scenarios (considering only Level 2 chargers) in Figure II.4.3. Adding chargers always reduces total waiting time, but the reduction is greater when the initial number of chargers is smaller. For example, in New York City, increasing the number of Level 2 chargers from 1 to 2 increases the levelized cost of charging for a private company by only \$0.01/kWh (from \$0.13/kWh to \$0.14/kWh), while the total waiting time decreases by 472 minutes in total. Increasing the number of Level 2 chargers from 19 to 20 still increases the levelized cost of charging for the same private company by only \$0.01/kWh (from \$0.28/kWh to \$0.29/kWh); however, the total waiting time is reduced by only 13 minutes.

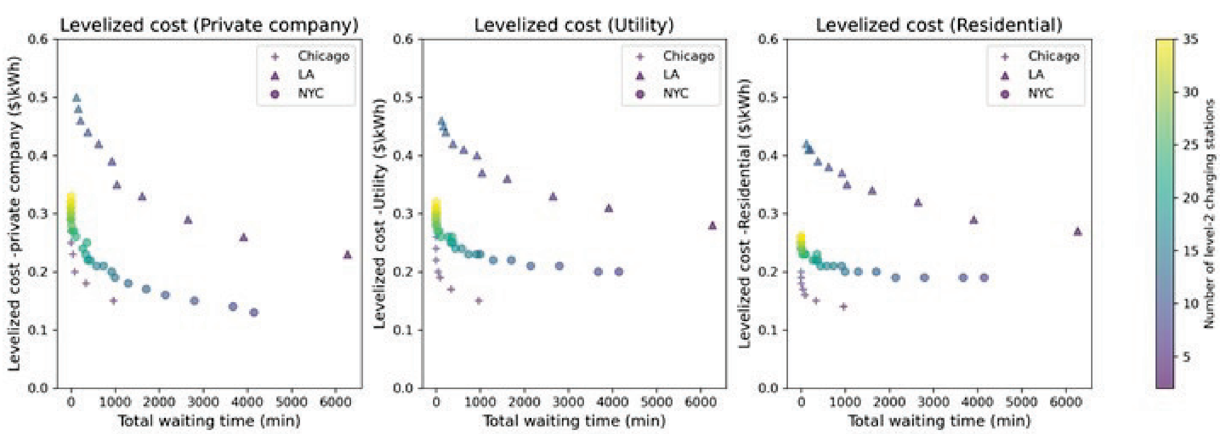

Figure II.4.3 Trade-offs between levelized cost of charging and total waiting time, when only Level 2 charging stations are installed in the MUD charging hub. Source: UIUC

The levelized cost of charging is shown to vary substantially with the number of chargers, hub location, and ownership model. When comparing the three business models, we find that the levelized cost of charging for a private company is higher than the cost for either a utility or the residential ownership model, except at low numbers of Level 2 chargers. The levelized cost in Los Angeles is, holding the other factors steady, higher than in New York City or Chicago, driven by a more expensive electricity rate in the state of California.

Equivalent Performance or Levelized Cost of Charging for a Mix of Level 2 and DCFC Stations in MUD Charging Hubs

The levelized cost of charging and total waiting time results are presented in Figure II.4.4 for 67 cases in New York City. These cases include combinations of two, three, and five DCFC stations with a variable number of Level 2 chargers. The equivalent charger configurations are based on hubs with alternate station configurations that either achieve the same levelized cost of charging or have the same total waiting time, respectively. The two charging hubs highlighted in the left figure have the same levelized cost of charging ($0.35/kWh) but different performance (7 minutes and 35 minutes in total). These points represent two different charging hub compositions: a case with two DCFC and 20 Level 2 chargers (red) and a case with three DCFC and six Level 2 chargers (green). Similarly, the three highlighted hubs in the right figure have the same performance (no delay) but different levelized costs of charging for compositions of two DCFC and 22 Level 2 chargers ($0.368/kWh), three DCFC and 13 Level 2 chargers ($0.394/kWh), and five DCFC and zero Level 2 chargers ($0.414/kWh). The first option seems preferable since it results in a lower cost of charging and no delays. Combining the results of charging scheduling management and technoeconomic assessment enables the investor to understand the implications of the MUD hub's parameters on system performance and levelized cost of charging.

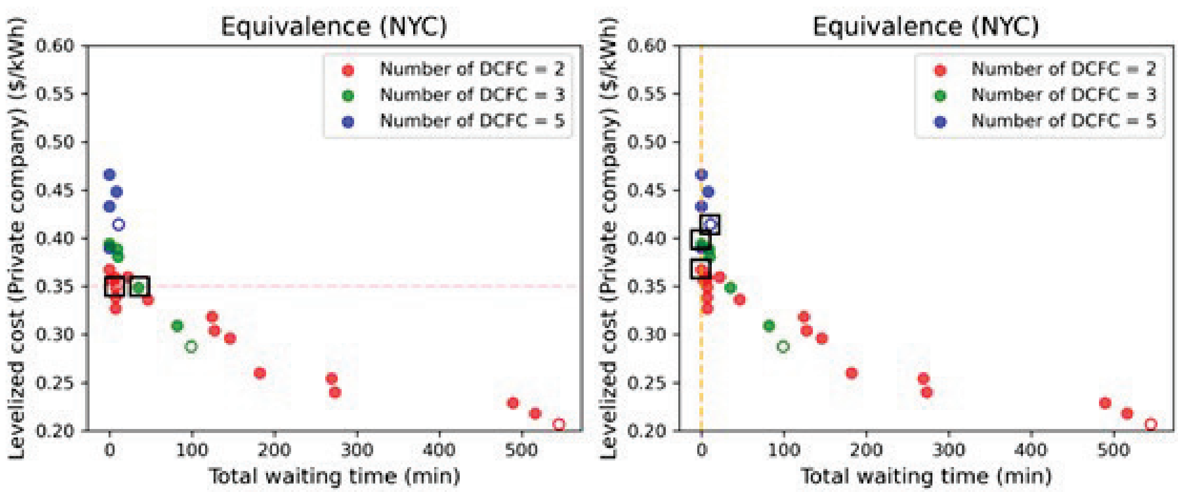

Figure II.4.4 Equivalent scenarios of charger power mixes in New York City. Source: UIUC

Charging Hub Sizing and Hub Power Profiles

For each hub, insights on the cost and the performance metrics for Level 2 chargers are provided in Table II.4.1. The levelized cost of charging is dependent on the ownership type, with each reflecting different electricity schedules, applicable costs, and internal rates of return (on capital costs), as outlined previously.

It can be seen from Table II.4.1 that when the charging hub size increases from small to medium, the total waiting time decreases drastically, and the levelized cost of charging for a private company often increases significantly. For example, in New York City, the total waiting time is reduced by 3,856 minutes, but the levelized cost of charging rises by 92%, 32%, and 22% for private company, utility, and residential ownership, respectively. However, when the New York City charging hub's size increases from medium to large, the decrease in charging time is only 271 minutes, and the levelized cost of charging rises by 36%, 44%, and 18% for private company, utility, and residential ownership, respectively. We observe similar trends in Chicago and Los Angeles. Private company ownership models have 25%, 55%, and 83% lower electricity rates ($/kWh) than residential and utility ownership models in Chicago, Los Angeles, and New York City, respectively.

Nevertheless, private company ownership models have demand charges in addition to volumetric electricity rates. The levelized cost of charging is especially sensitive under private company ownership because of a high internal rate of return (secondarily) applied to capital costs and an expensive demand charge (primarily) for the commercial electricity schedule, which the residential and utility ownership models avoid (they have residential electricity schedules). Further, private-company-owned hubs in New York City and Los Angeles have expensive demand charges, so they are more sensitive to increases in chargers and size than Chicago hubs.

Table II.4.1 Small, Medium, and Large Charging Hubs in Chicago, New York City, and Los Angeles Scenarios for Level 2 Chargers

Study Area	Charging Hub Size	Number of Level 2 Chargers	Total Waiting Time (min)	Levelized Cost of Charging ($/kWh)		
				Private Company	Utility	Residential
Chicago	Small	2	1,853	0.15	0.15	0.14
	Medium	5	46	0.24	0.21	0.17
	Large	8	0	0.30	0.26	0.21
New York City	Small	8	4,147	0.13	0.19	0.18
	Medium	21	271	0.25	0.25	0.22
	Large	35	0	0.34	0.31	0.26
Los Angeles	Small	3	6,270	0.24	0.28	0.27
	Medium	8	927	0.39	0.40	0.38
	Large	13	124	0.51	0.47	0.43

The average 48-hour power profiles of small, medium, and large charging hubs are presented for various charging station configurations in Figure II.4.5. The large charging hubs have higher peak power than the small and medium hubs but have shorter total operating periods. When considering only Level 2 chargers (top row), for instance, in the scenario of New York City (right column), the maximum power is 52.8 kW, 103.95 kW, and 118.8 kW for a small, medium, and large charging hub, respectively. Comparing hosting only Level 2 chargers (top row) to hosting only DCFC ones (bottom row), the power profiles are similar because their shapes are determined by the travel patterns of EV owners. However, when charging hubs host DCFC, the profiles shrink since the EVs charge faster. The peak power of DCFC stations is much greater than that of Level 2 chargers. The power peaks often occur between 16:00 and 20:00 hours (time index 960–1,200), which coincides with the commuting patterns of MUD residents.

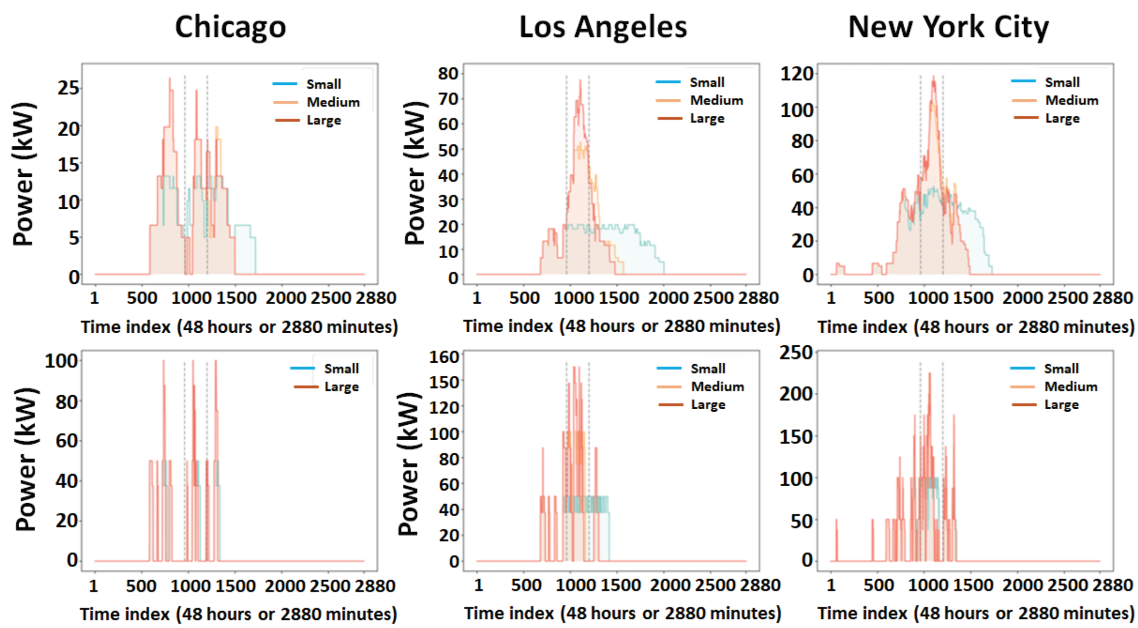

Figure II.4.5 Average 48-hour load profiles of small, medium, and large charging hubs in Chicago, Los Angeles, and New York City. Source: UIUC

Conclusions

Apartment complex residents who are prospective EV owners face major obstacles associated with home charging infrastructure installation and access. Our research evaluates the viability of community charging hubs for MUDs by leveraging algorithms for centrally shared charging session scheduling and technoeconomic assessment. The rule-based heuristic algorithm proposed to solve this management problem provides high-quality charging schedule solutions when compared to an unmanaged first-come-first-served charging scheme. Determining a charging hub's performance and economics uncovers the trade-offs between the hub's total waiting time and its levelized cost of charging. This project provides equivalent charger setups based on levelized cost of charging and total waiting time; this information can help various investors determine which setups will satisfy their goals. Our study creates new knowledge in the electrified transportation field by introducing new computational tools and presenting practical strategies and novel insights, all of which can be used to expand access to chargers in MUDs. Future studies should focus on modeling networks of shared community charging hubs for cities with a high percentage and density of MUD residents, leveraging insights and data from this study.

Key Publications

1. Zhang, Ruolin, Noah Horesh, Eleftheria Kontou, and Yan Zhou. 2022. "Electric vehicle community charging hubs in multi-unit dwellings: scheduling and techno-economic assessment." Available at SSRN 4246024.

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Acknowledgements

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II.5 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 (FY22): $179,656 DOE share: $150,156 Non-DOE share: $29,500
Project Funding (Overall): $451,852 DOE share: $339,449 Non-DOE share: $52,403

Project Introduction

According to the U.S. Environmental Protection Agency, medium- and heavy-duty trucks accounted for 26% (39.6 million metric tons) of transportation-related greenhouse gas emissions—more than aircraft, rail, and maritime emissions combined [1]. Therefore, there is a significant opportunity to reduce greenhouse gas emissions by electrifying heavy-duty commercial vehicle fleets. As demand for consumer electric vehicles (EVs) has drastically increased in recent years, original equipment manufacturers have been working to bring heavy-duty EVs to market to compete with Class 6–8 diesel-powered trucks. Many high-profile companies, such as PepsiCo, Walmart, Amazon, and the United Parcel Service, have publicly committed to begin electrifying their fleet operations but have yet to implement EVs at scale because of their limited range, long charging times, sparse charging infrastructure, and lack of data from in-use operation. Thus far, EVs have been disproportionately implemented by larger fleets with more resources. To aid fleet operators, it is imperative to develop tools to evaluate the electrification potential of heavy-duty fleets. However, commercially available tools, designed mostly for light-duty vehicles, are inadequate for making electrification recommendations tailored to a fleet of heavy-duty vehicles. The main challenge is that light-duty vehicle tools do not estimate real-time vehicle mass, a factor that has a disproportionate impact on the energy consumption of large commercial vehicles. To address these concerns and to enable large-scale EV adoption, this project is developing a publicly available Heavy-Duty Electric Vehicle Integration and Implementation (HEVII) tool, both to assess heavy-duty EV suitability and to identify necessary infrastructure improvements, both public and private.

The HEVII tool advances the state of the art in evaluating electrification potential and infrastructure requirements for fleets of commercial vehicles. Data collection has been executed in collaboration with a technical partner, Geotab, an industry-leading cloud-based datalogging service provider. The project has obtained the required input data from existing telematics infrastructure on commercial vehicles; the data source is a PepsiCo fleet of vehicles, and the data have been obtained in compressed form using non-uniform sampling and historical summaries [2]. Sparse ground-truth data for all input drive cycles are used for payload mass prediction. The vehicle model developed from the estimated mass is used to evaluate electrification potential and EV component sizing. This preliminary data analysis and component sizing is conducted in collaboration with the National Renewable Energy Laboratory (NREL). The project team is also using a novel charger placement algorithm to identify optimal charger locations to maximize the number of routes that are viable for EVs. A thorough review is included in a recent paper [2], which discusses a standard framework used in the HEVII tool for solving the charger placement problem. Additionally, useful analytics on infrastructure development cost, wait times, and spatiotemporal energy requirements are provided. The tool currently encompasses three primary stages: (1) mass estimation, (2) EV battery and charger sizing, and (3) charger placement and cost analysis. Figure II.5.1 represents the interconnection between these stages.

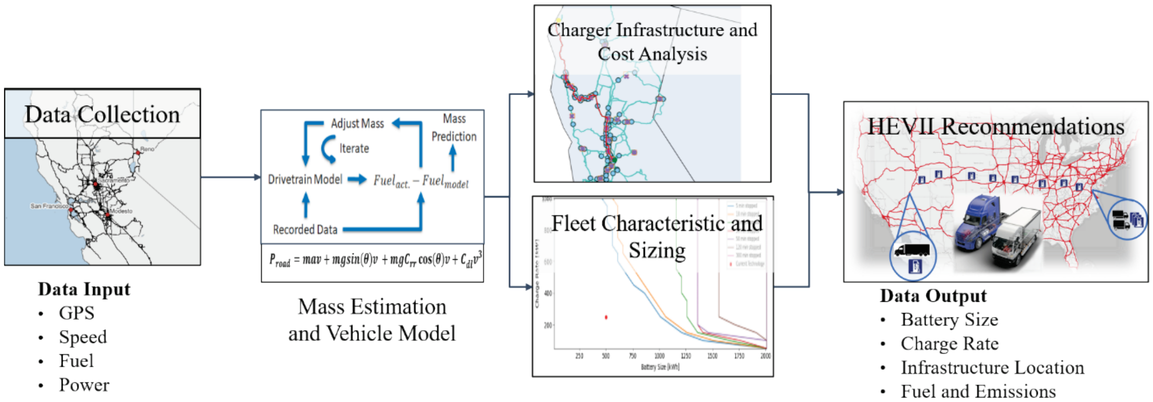


Figure II.5.1 Depiction of the HEVII tool stages: data input, analysis, and resulting data output. Source: University of Minnesota

Objectives

The primary aim of the proposed work is to develop an innovative and easy-to-use tool to evaluate the electrification potential of commercial fleets. The main objectives of the project are to:

- Conduct a vehicle-duty-cycle analysis of two regional Class 6–8 commercial vehicle fleets.
- Develop a model using a novel mass prediction algorithm that uses fleet trajectory data to estimate EV range and applicability.
- Develop an integrated charger location estimation tool to determine infrastructure requirements for fleets and municipal corridors.
- Validate the developed tool using data from in-use EVs operating in two metropolitan regions.

All objectives but the last have seen significant progress or been completed.

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 the battery size and en-route charging locations required to complete the same work presently undertaken by those fleets. 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 en-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 the accuracy of EV energy use estimation, 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

In the HEVII tool, a simplified vehicle model is developed that estimates instantaneous power requirements to get EV energy consumption and energy recapture from regenerative braking using a road-load model. Mass is predicted using a data-driven approach to improve energy estimates derived from the vehicle model. A sweep of battery size and charge rate is used to determine which combination of parameters will allow an equivalent EV to complete its daily assignment without having a state of charge violation. A novel clustering-based method is used to place two charging stations, and a cost model is used to calculate the resultant infrastructure-related financial costs. The methods corresponding to each objective are described below.

Duty Cycle Analysis and Charger Sizing

Expected duty cycle is a key factor in determining the potential to electrify a vehicle. With EV powertrains becoming more efficient and batteries having relatively low capacities and slow charge rates, successful heavy-duty EV implementations are highly dependent on how the vehicle is used. Easily calculated metrics such as daily distance, average speed, idle time, and energy intensity can quickly identify or rule out a vehicle as a candidate for electrification. In general, vehicles with lower speeds, short daily distances, and operation in a moderate climate are conducive to electrification.

The HEVII tool initially conducts several analyses to determine electrification potential for the specific fleet by inspecting various driving patterns. Figure II.5.2 presents the aggregated vehicle statistics by utilizing the cloud-connected service trip summary table. For instance, daily distance provides insights into EV selection by determining which driving ranges are suitable. Similarly, the percentage of time idle can show the distribution of a vehicle's time stopped, which assists in determining charging opportunities.

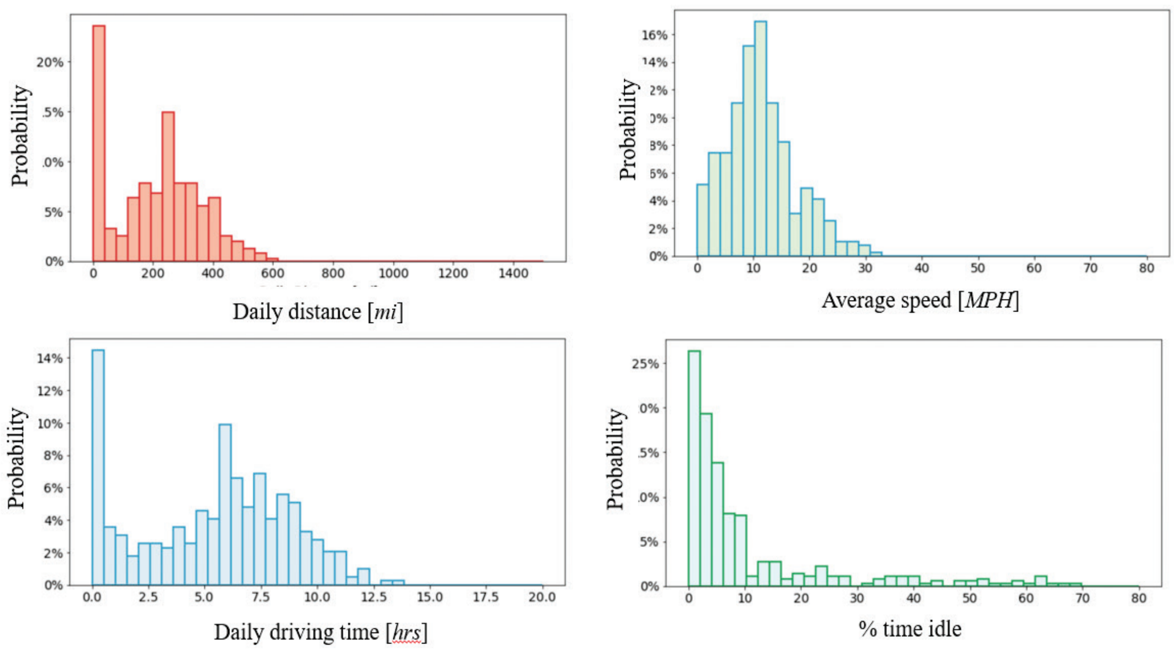


Figure II.5.2 Aggregated vehicle statistics using a cloud-connected service trip summary table. Source: University of Minnesota

After examining high-level statistics and dwell periods, a detailed battery size and charge rate scenario analysis is constructed by incorporating the existing vehicle engine energy production and a simplified EV model. Figure II.5.3 displays the relationship between battery size and charge rate for a Class 8 tractor, assuming the vehicle can charge when stopped for the given length of time or longer. Based on this analysis, and assuming a minimum stop duration of four minutes, no adequate combination of battery size and charge rate exists within the bounds of the current technology. Nevertheless, the outputs of this analysis show the tradeoffs between vehicle specifications that would allow for electrification as the technology advances.

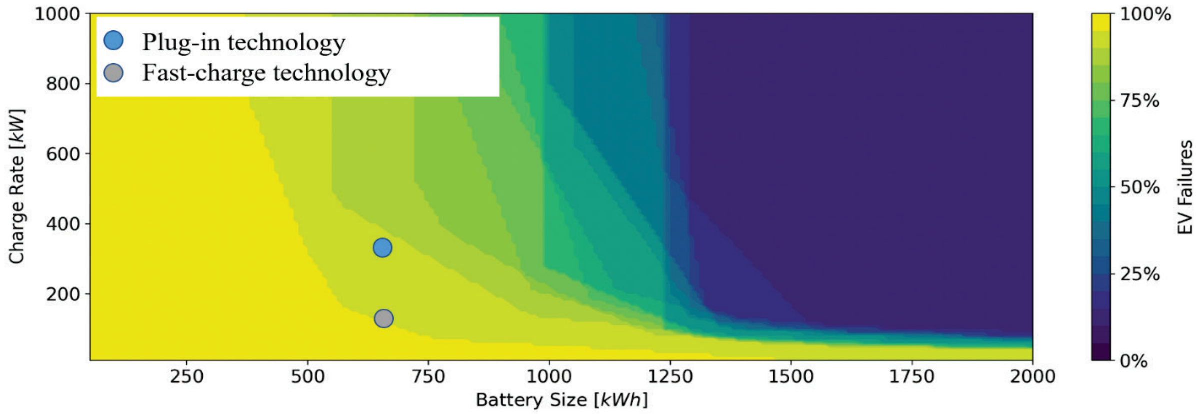


Figure II.5.3 Battery estimates with respective EV failure rates. Source: University of Minnesota

Mass Estimation

As driving data are input into the HEVII tool, instantaneous power demands for the vehicles are estimated using a road-load equation model, as in Equation II.5.1.

$$P_{road} = [ma + mgsin\theta + mgC_{rr} + 1/2\rho Av^2]v \qquad (II.5.1)$$

Vehicle speed (v), road grade (θ), and acceleration (a) can often be obtained from on-board diagnostics (OBD) data. Air density (ρ) and gravitational acceleration (g) may be assumed constant. Key vehicle parameters, including the drag coefficient (C_d), frontal area (A), and coefficient of rolling resistance (C_{rr}), may be estimated from the collected data by fitting the model to ground-truth energy measurements (i.e., fuel used), assuming the vehicle mass (m) is known. If the mass is not known for any of the input data, a standard Class 8 truck model can be used to correct the parameter in real time by comparing the actual and model-estimated fuel usage. If mass is known for a subset of the input data, those data may be used to train a data-driven model such as a k-nearest neighbors (kNN) regressor model or a neural network-based model if there are sufficient training data. For the example dataset used throughout this work, a small subset—roughly 10% of the total input data—contained ground-truth payload mass values matched from a secondary source. Because the input data were collected at a non-uniform sampling frequency, the model-based mass estimation method was found to be inaccurate. Because of the limited amount of training data, a kNN regressor model was trained as proposed by Eagon et al. [3]. With this model, mass is predicted based solely upon the similarity of an input datapoint to datapoints in the training set, using a distance-weighted average mass value as the prediction. Figure II.5.4(a) shows simple depictions of the model-based and Figure II.5.4(b) the kNN-based mass estimation methods.

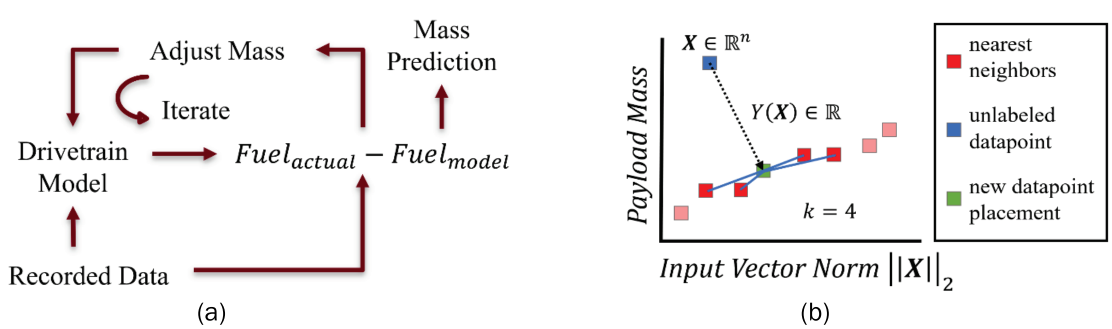
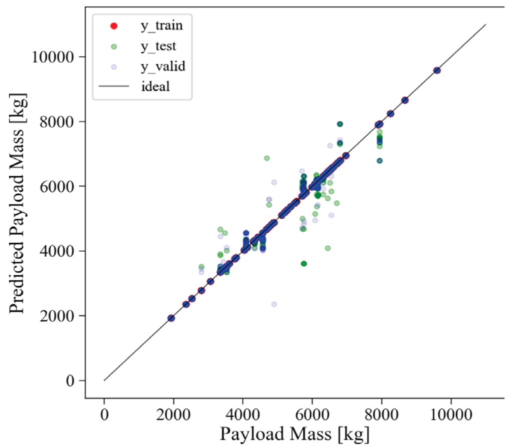
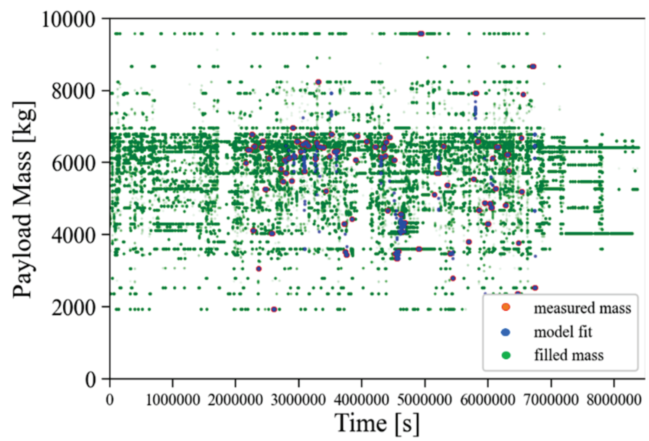


Figure II.5.4 (a) Model-based mass estimation and (b) data-driven mass estimation. Source: University of Minnesota

The kNN regressor model was chosen to estimate mass because of the relatively small set of input data with a mass measurement available—847,432 out of 8,381,548 total datapoints (or 10.11%)—and because the data were not sampled at a high enough frequency for model-based mass estimation to perform adequately. The kNN regressor was used with 60% of the labeled data for training and 20% for testing, reserving 20% for validation with a k-value of 2. The performance with k = 2 was impressive, with a coefficient of determination (R^2 score) of 0.999, as shown in Figure II.5.5(a). The historical data, along with the predicted mass, are shown in Figure II.5.5(b).



(a)



(b)

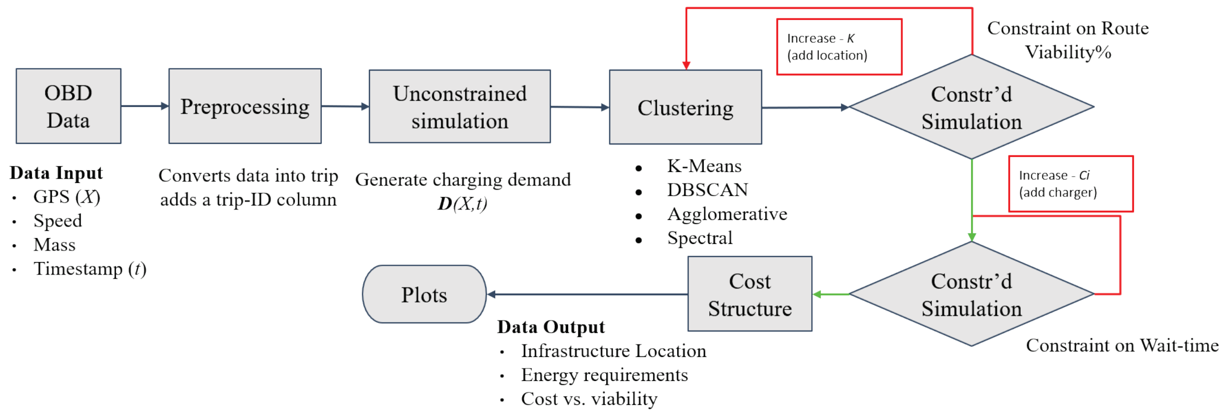
Figure II.5.5 (a) Results after fitting kNN regressor and (b) the predicted mass history. Source: University of Minnesota and NREL

Charger Placement and Cost Analysis

This section of the tool is used to assign charger station location, the number of chargers for each selected location, and the cost of deploying this infrastructure. The charger station locations determine route-wise electrification viability, which considers the spatial distribution of charging demand. The number of chargers per station determines the actual ideal time for the trucks. The spatiotemporal distribution of charging demand is accounted for in this section. Finally, a cost structure, as shown in Table II.5.1, is used to estimate the total cost of infrastructure deployment based on Nicholas 2019 [4]. The schematics and overall flow of data are represented in Figure II.5.6. The simultaneous application of statistical methods and the use of physics-based models lead to high-accuracy predictions and are useful for reducing range anxiety typically associated with EVs.

Table II.5.1 Cost Per Charger for Purchasing and Deploying Charging Stations

Expenditure per Station	Chargers per Station			
Expense Type	1	2	3–5	6–10
Charger Hardware	$140,000			
Labor	$28,000	$22,500	$16,500	$10,500
Installation Material	$38,000	$30,500	$23,000	$15,500
Fees	$500	$400	$300	$200

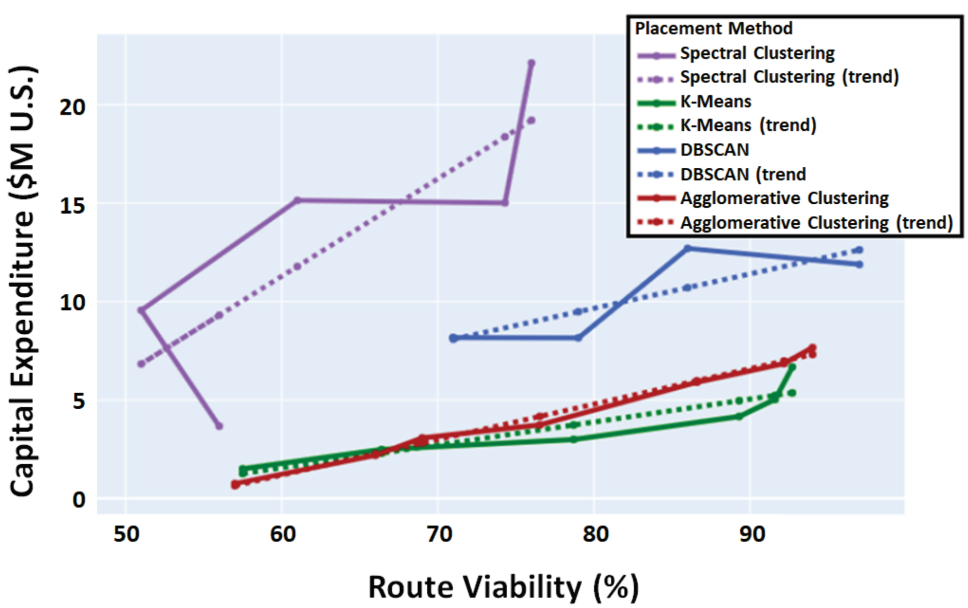


GPS = global positioning system; ID = identification; DBSCAN = density-based spatial clustering of applications with noise; Ci = initial chargers

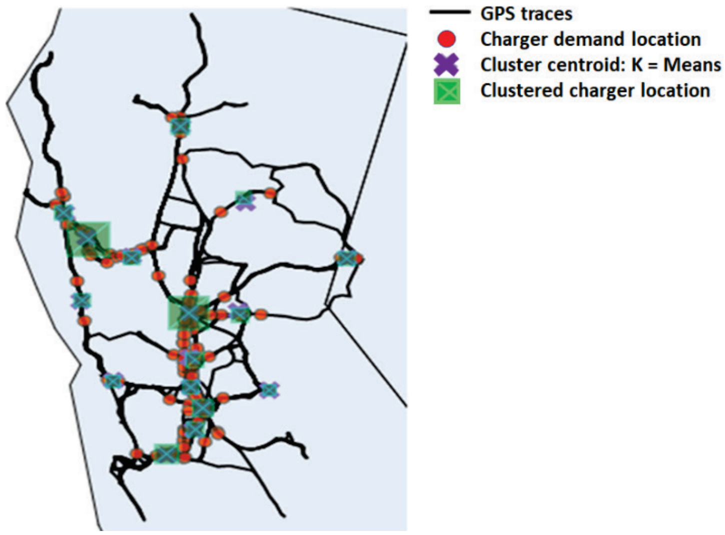
Figure II.5.6 Schematic diagram of charger station location problem. Source: University of Minnesota

In the unconstrained simulation, the truck is assumed to start at a maximum state of charge. A physical model estimates the energy used and the corresponding change in the state of charge. The set of GPS coordinates where the vehicles are required to charge to complete all routes is assigned as spatiotemporal charging demand. Various clustering methods were benchmarked for the "hub and spoke" type of dataset. The most effective method, k-means, with varying values of cluster centers, is used to generate the charger locations. In the constrained simulation stage, the vehicles are allowed to charge only within five miles of a designated charging station. In addition to this, a 15-minute maximum wait-time constraint is applied to determine the number of chargers required at each station.

The two primary outputs of this module are the chart showing the tradeoff between cost and percentage of overall route completion, shown in Figure II.5.7(a), and the charger station location with the spatiotemporal distribution of energy requirements, highlighted in Figure II.5.7(b). The green square size in Figure II.5.7(b) is indicative of cumulative energy demand at the location.



(a)



(b)

Figure II.5.7 (a) Capital expenditure analysis with various clustering methods and (b) charging stations for k-means clustering of 16 clusters. Source: University of Minnesota

Conclusions

The open-source HEVII tool remains under development and is expected to be available as a prototype at the end of this two-year project. The project teams at the 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.

Key Publications

1. Eagon, Matthew, Setayesh Fakhimi, George Lyu, Audrey Yang, Brian Lin, and William F. Northrop. 2022. “Model-Based Framework to Optimize Charger Station Deployment for Battery Electric Vehicles.” 2022 IEEE Intelligent Vehicles Symposium (IV), Aachen, Germany: 1639–1648. https://doi.org/10.1109/iv51971.2022.9827442.

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3. Eagon, Matthew, Setayesh Fakhimi, Adam Pernsteiner, and William F. Northrop. 2022. “Mass Detection for Heavy-Duty Vehicles Using Gaussian Belief Propagation.” In 2022 IEEE Intelligent Vehicles Symposium (IV), Aachen, Germany: 1655–1661. https://doi.org/10.1109/IV51971.2022.9827370.

4. Nicholas, M. 2019. “Estimating electric vehicle charging infrastructure costs across major US metropolitan areas.” Working Paper 2019-14. International Council on Clean Transportation, August.

Acknowledgements

The project team would like to thank project partners, Hani Hawari of Geotab and Garrett Boylen and Adrian Rodriguez from PepsiCo, for their contributions to the project. In addition to the principal investigator's work, other notable contributions to the work were made by Aaditya Badheka and Matthew Eagon (University of Minnesota – Twin Cities, Department of Mechanical Engineering), Setayesh Fakhimi (NREL), Peter Wiringa (University of Minnesota – Twin Cities), and Eric Miller and Andrew Kotz (NREL).

II.6 Micromobility Screening for City Opportunities Online Tool (University of Washington)

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Start Date: October 1, 2020 End Date: December 31, 2022
Project Funding: $145,229 DOE share: $129,229 Non-DOE share: $16,000

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 the U.S. Department of Energy (DOE) need a tool that can screen cities and neighborhoods to identify areas with a high opportunity for micromobility to gain market share, improve accessibility, and/or increase mobility energy productivity relative to incumbent modes. Such a tool will allow for the deployment of micromobility resources 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 the associated impacts of micromobility services. The Micromobility Screening for City Opportunities Online Tool (SCOOT) aims to 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 to facilitate further development by DOE, national labs, or the private sector.

Approach

Work in the previous fiscal year had focused on gathering necessary background information, designing and programming a web survey, and generating a synthetic population sample. Activities in the most recent fiscal year included fielding the web survey to collect data, estimating models of travel behavior using the resulting data, integrating these sub-models into the SCOOT framework, and validating its outputs. Remaining work involves completing the validation and calibration of the SCOOT modeling framework and deploying it as an online tool.

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

- Administrating a stated preference/revealed preference (SP/RP) questionnaire.

- Processing survey data and modeling mode choices, including micromobility options conditional on attributes of the mode, individual, and environment.
- Refining the synthetic population to represent travelers across census tracts in all MSAs using the survey data and including variables identified as influential in the survey and choice modeling.
- Modeling tours and destination choices using National Household Travel Survey (NHTS) data to generate daily travel activities for individuals in the synthetic population sample [1].
- Integrating the models into the SCOOT framework and applying them to each individual in the synthetic sample to predict the utility of each mode and the number of micromobility trips.
- Organizing and analyzing observed micromobility ridership data at the census-tract level and measuring walking access time.

Efforts in the remainder of the project involve completing model calibration and validation and deploying and testing SCOOT as an online tool. The calibrated and validated SCOOT 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 greenhouse gas emissions will be conducted, with and without micromobility services available. Finally, the SCOOT framework will be implemented into an interactive web-based tool, then tested and refined.

Results

A multinomial logit mode choice model was built using Biogeme, employing 8,808 choice task responses from 1,753 respondents to the SP/RP survey. The outcome variable is mode choice, including all micromobility modes (i.e., shared e-scooter, dockless bikeshare, docked bikeshare, and shared e-scooter used to access transit) and conventional modes (i.e., car, transit, ride hailing, walk, and bike). In our model, the disutility of travel time is assumed to be specific to each alternative, except that bike, dockless bikeshare, and docked bikeshare modes are assumed to share the same travel time coefficient. Travel cost divided by income was used only for micromobility modes since the travel costs of respondents' current modes were not available from the survey. Coefficients for trip purposes were estimated for all travel modes and were forced to be the same for all micromobility modes. Bike lane availability and precipitation were included as predictors for biking and all micromobility modes and were assumed to have the same effect on each of these modes. Access walking distance was included for all micromobility modes and docked bikeshare had an additional variable for the walking distance from the drop-off dock to the final destination. A dummy variable indicating autonomous technology (AT) and waiting time for hailing an autonomous e-scooter were included in utility functions for e-scooter and e-scooter + transit modes. This allowed us to investigate whether a user's ability to summon an e-scooter and have it autonomously come to the user would affect usage. Model results are presented in Table II.6.1.

The cleaned survey data were also employed in the population synthesis procedure. This process was performed at the geographic levels of MSAs and census tracts. Daily weekday activity tours were then sampled from NHTS to provide the input trip data required for applying the mode choice model. Individual tours in the NHTS were clustered into seven types using k-means. A multinomial logit model was then constructed using socioeconomic data from NHTS and used to predict probabilities of a given synthetic individual undertaking each type of tour. This model was validated using 10-fold cross-validation on the full NHTS tour dataset (n=173,704), which provided an average prediction accuracy of 38%, an improvement of 24% over randomly assigning tours to individuals.

Table II.6.1 Multinomial Logit Choice Model Results for All Travel Modes

Variable	Estimate	Std. Error	Pr(>|z|)	Significance
Car				
Travel time (min)	-0.069	0.008	<0.001	***
Household size	-0.279	0.029	<0.001	***
Transit				
Constant	-2.190	0.404	0.027	**
Travel time (min)	-0.029	0.004	<0.001	***
Trip purpose (ref: home-based work)				
Home-based other	0.544	0.565	0.336	
Home-based shop	0.835	0.637	0.190	
Home-based social	1.770	0.751	0.018	**
Not home-based	0.934	0.480	0.052	*
Ridehailing				
Constant	-3.330	1.610	0.039	**
Travel time (min)	-0.030	0.008	<0.001	***
Trip purpose (ref: home-based work)				
Home-based other	0.843	0.989	0.394	
Home-based shop	2.080	1.550	0.178	
Home-based social	1.460	1.010	0.148	
Not home-based	1.070	0.773	0.164	
Employment(1: employed; 0: else)	2.510	1.530	0.102	
Household size	-0.514	0.245	0.035	**
Walk				
Constant	-2.780	0.326	<0.001	***
Travel time (min)	-0.008	0.004	0.054	*
Trip purpose (ref: home-based work)				
Home-based other	0.575	0.438	0.190	
Home-based shop	0.764	0.386	0.048	**
Home-based social	0.517	0.478	0.279	
Not home-based	1.950	0.392	<0.001	***
Bike				
Constant	-1.750	0.248	<0.001	***

Variable	Estimate	Std. Error	Pr(>|z|)	Significance
Travel time (min)	-0.015	0.002	<0.001	***
Trip purpose (ref: home-based work)				
Home-based other	-0.281	0.278	0.313	
Home-based shop	0.195	0.283	0.491	
Home-based social	-0.417	0.343	0.224	
Not home-based	1.220	0.228	<0.001	***
Bike lane (1: less than 50% bike lane available; 0: else)	-0.117	0.071	0.096	*
Precipitation (ref: no rain)				
Heavy rain	-0.613	0.087	<0.001	***
Light rain	-0.434	0.085	<0.001	***
E-scooter				
Constant	-2.320	0.204	<0.001	***
Travel time (min)	-0.043	0.005	<0.001	***
Travel cost/individual income in thousands (unitless)	-0.799	0.117	<0.001	***
Trip purpose (ref: home-based work)				
Home-based other	-0.015	0.123	0.901	
Home-based shop	0.080	0.125	0.524	
Home-based social	-0.238	0.138	0.085	*
Not home-based	0.614	0.101	<0.001	***
Bike lane (1: 50% or less bike lane available; 0: else)	-0.117	0.071	0.096	*
Precipitation (ref: no rain)				
Heavy rain	-0.613	0.087	<0.001	***
Light rain	-0.434	0.085	<0.001	***
Access walking time (min)	-0.075	0.012	<0.001	***
Autonomous (1:AT available; 0:else)	0.071	0.073	0.328	
AT Waiting time (min)	-0.029	0.017	0.085	*
Personal bike ownership (1: bike owner; 0:else)	0.505	0.082	<0.001	***
Employment(1: employed; 0: else)	0.433	0.126	<0.001	***
Population density at home zip code (1000 people/sq.mile)	0.006	0.003	0.051	*
Dockless bikeshare1				
Constant	-2.340	0.202	<0.001	***
Travel time (min)	-0.015	0.002	<0.001	***

Variable	Estimate	Std. Error	Pr(>|z|)	Significance
Docked bikeshare1				
Constant	-2.870	0.211	<0.001	***
Travel time (min)	-0.015	0.002	<0.001	***
Drop-off walking time (min)	-0.071	0.027	0.009	***
E-scooter + transit2				
Constant	-2.520	0.199	0.027	**
E-scooter travel time (min)	-0.043	0.005	<0.001	***
Transit travel time	-0.029	0.004	<0.001	***

N=8,088 choice tasks log likelihood (LL)=-5742.142
**: 2-tail significance at α=0.10*
***: 2-tail significance at α=0.05*
****: 2-tail significance at α=0.01*

Note 1: Additional variables include travel cost/individual income in thousands, trip purpose, bike lane, precipitation, access walking time, personal bike ownership, employment, and population density at home zip code. These variables share the same coefficients as those estimated for the e-scooter mode, omitted from the table for brevity.

Note 2: Additional variables include travel cost/individual income in thousands, trip purpose, bike lane, precipitation, access walking time, autonomous, AT waiting time, personal bike ownership, employment, and population density at home zip code. These variables share the same coefficients as those estimated for the e-scooter mode, omitted from the table for brevity

To generate tours for the synthetic population, individuals were sampled from the synthetic population, and then their tour type probabilities for each tour cluster were calculated using the multinomial logit model, conditional on their socioeconomic characteristics. Then, a tour was sampled from a cluster randomly according to these probabilities. The NHTS expansion weights were applied during the clustering process and when sampling a tour from a cluster type. This ensured that tours were sampled in proportion to their prevalence in the population. Last, trips in each tour were assigned to destination tracts randomly based on the distance of the trip reported in NHTS and on the home tract of the synthetic individual.

The University of Washington team also revisited the data sources being used for validation of the SCOOT framework. After reviewing all of the datasets previously identified as well as those documented in a report from Argonne National Laboratory [2], the team found at least one usable dataset from each of the six cities on which the SCOOT project is focusing. For the dataset to be considered "usable," it had to have regular updates and to include data from 2022. In addition, there must be some geographic location given for the start and end location of each trip. Usable datasets are summarized in Table II.6.2 and will be used in building the mapping tool.

Table II.6.2 Summary of Usable Micromobility Trip Datasets

City	Companies Operating	Dataset Link	Vehicles Included	Dataset Time Period Start	Dataset Time Period End	Spatial Resolution	Update Frequency
Los Angeles	Bird, Lime, Spin, LINK, Wheels, Lyft, Metro	Los Angeles Dataset	Divvy Bikes only	7/7/2016	6/30/2022	GPS	Quarterly
Chicago	Divvy, Lime, Spin, LINK	Chicago Dataset	Divvy Bikes only	1/24/2020	6/30/2022	GPS	Monthly

Austin	Bird, Lime, Link, Wheels	Austin Dataset	Bird, Lime, Link, Wheels	4/3/2018	4/4/2022	Census Tracts	Updates ended 3/22
San Francisco	Lyft (Bay Wheels), Lime, Spin	San Fransisco Dataset	Bay Wheels Bikes only	1/1/2018	6/30/2022	GPS	Monthly
Washington DC	Lyft (Capital Bikeshare), Jump (Lime), Bird (Scoot), Skip, Spin, Helbiz	Washington DC Dataset	Capital Bikeshare Bikes only	9/20/2010	6/30/2022	GPS	Monthly
Boston	Lyft (BLUE-bikes), Lime, Bird	Boston Dataset	BLUEBikes Bikes Only	1/1/2015	6/30/2022	GPS	Monthly

Conclusions

The key accomplishments completed in FY 2022 include administering the SP/RP online survey; modeling mode choices including micromobility options conditional on attributes of the mode (e.g., travel time, access distance, cost), the individual (e.g., income, employment status, personal bike ownership), and the environment (e.g., density, presence of bike lanes, weather); and generating simulated daily travel activities for individuals in the synthetic sample population. Alongside several other tasks completed during this period, the project activities have provided the necessary building blocks for completing the key remaining objectives: (1) calibrating and applying the SCOOT framework, which will evaluate and display the market potential, accessibility, energy productivity, and emissions savings associated with micromobility services, and (2) implementing SCOOT as an open-source, web-based tool.

Key Publications

1. Zou, T. and D. MacKenzie. 2023. "Bike Lanes and Ability to Summon an Autonomous Scooter Can Increase Willingness to Use Micromobility." TRB Paper No. 23-04793. Transportation Research Board 102nd Annual Meeting, January 2023.

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

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1. National Household Travel Survey, https://nhts.ornl.gov

2. Rush, L., M. Cribioli, D. Gohlke, Y. Zhou, J. Kelly, and X. Wu. 2022. "Shared Mobility Data Availability and Usage Trends." Argonne National Laboratory, No. ANL/ESD-22/9.

Acknowledgements

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

III Powertrain Choice and Infrastructure Use

III.1 Transportation Energy Evolution Modeling (TEEM) Program (Oak Ridge National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (FY22): $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 is important to the U.S. Department of Energy's mission and to its stakeholders, enabling both government and industry to better understand and quantify the future value of ongoing research and development (R&D). Technology impacts (e.g., energy consumption, consumer costs, and greenhouse gas [GHG] emissions) are often used to justify and prioritize R&D investments in advanced vehicle technologies. Quantifying such impacts requires an estimation of consumer adoption of the technologies. However, consumers and engineers/scientists may view technologies differently. 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 spreadsheet-based Market Acceptance of Advanced Automotive Technologies (MA3T) model and its derivative models to simulate market penetration and dynamics in transitions toward energy-efficient vehicle and mobility technologies. The MA3T model outputs annual sales share and energy usage of either a vehicle or mobility technology (e.g., 42 V mild hybrid, 200-mile battery electric vehicle [BEV], or automated shared mobility). Model inputs include consumer segmentation and attributes (such as consumer driving patterns, and technology attitudes), technology cost and performance, infrastructure availability and prices, and government incentives. All of these inputs can be easily changed in the model, constructed based on the Microsoft Excel® VBA.

The success of the Vehicle Technologies Office (VTO) Analysis investment in the MA3T model has been evidenced by expanded sponsorship both for the application of MA3T and for its adaption for other purposes; sponsors are the International Institute for Applied Systems Analysis and the DOE Office of Energy Efficiency and Renewable Energy, including VTO Energy Efficient Mobility Systems, the Hydrogen and Fuel Cell Technologies Office, and the Bioenergy Technologies Office. The TEEM team has published over 90 peer-reviewed articles (https://teem.ornl.gov/publications.shtml), including four during Fiscal Year (FY) 2022.

Objectives

The objectives of the TEEM project are to:

- Develop a user-friendly, useful, and credible simulation tool in support of techno-economic analysis with respect to energy-relevant vehicle technologies.
- Close key knowledge gaps in fundamental issues.
- Advance discussions of vehicle technologies through publications.
- 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. The nested multinomial logit methodology is on the basis of the multinomial logit model, and it allows inter-dependent relations across different subcategories or nests. Therefore, the probability results are from a multi-level decision. 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 simulation year. Model inputs include consumer segmentation and attributes, technology cost and performance, infrastructure availability and prices, and government incentives.

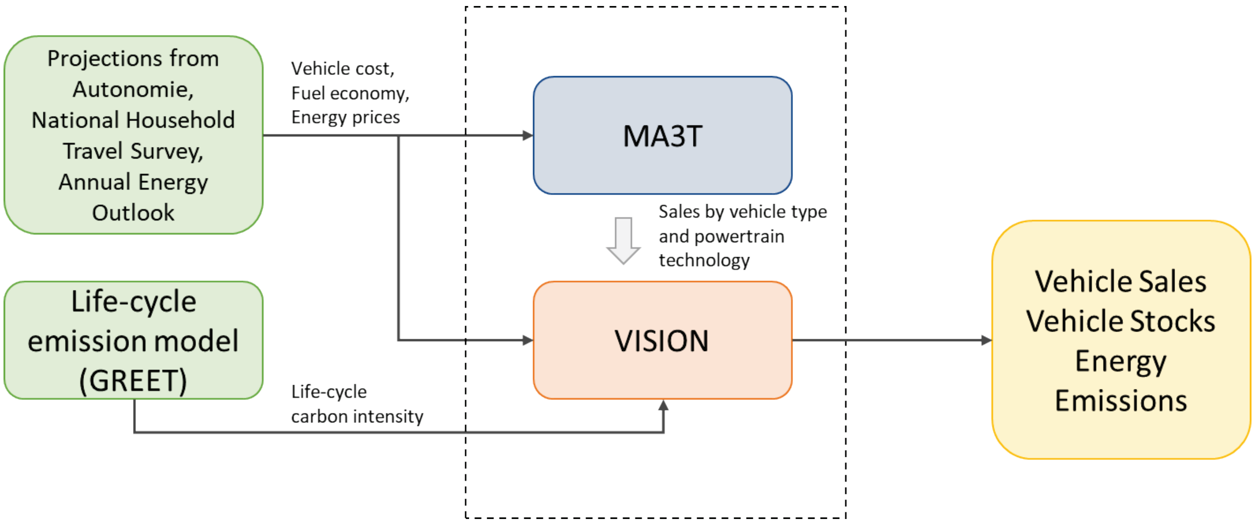
The MA3T and its derivative models, such as the MA3T-mobility and the TruckChoice model, are structured to accept data, targets, and assumptions from VTO R&D programs, including but not limited to program targets of VTO, the Hydrogen and Fuel Cell Technologies Office, the Bioenergy Technologies Office, projected energy prices from various Annual Energy Outlook scenarios, industry inputs on battery cost and fuel economies, state-level plug-in electric vehicle incentives, regional deployment of public chargers and, in some cases, the hypothetical deployment of extreme fast charging. The TEEM program has also developed new methods to quantify certain utility components in consumer choice, such as range limitation cost and refueling inconvenience.

In FY 2022, the team’s primary focuses were (1) to adopt the MA3T model to project GHG emissions from the U.S. light-duty vehicle (LDV) market under different technology and policy scenarios and (2) to understand the impacts of consumer heterogeneity on measuring average vehicle fuel economy in the market. Consumer heterogeneity is variation among users in terms of their travel patterns, household incomes, technology attitudes, charging behaviors, etc. In addition, to implement the MA3T-used vehicle model, the team updated and calibrated the vehicle scrappage rates and used vehicle price elasticities in the U.S. market with the most recent data sources and public literature.

Results

Scenario Analysis for Achieving the Net-zero GHG Emissions Target in the U.S. LDV Market Through Electrification

Considering only electrification pathways, this study uses publicly available tools to quantify the policy gaps that hinder LDVs from achieving the net-zero GHG emissions target in nine vehicle penetration cases under two electricity mix scenarios, including the U.S. administration’s decarbonization strategy: 100% clean electricity by 2035. MA3T and Verifiable Fuel Cycle Simulation (VISION) are the tools used. The team employs them to study vehicle market penetration, examine fleet accounting, and conduct life cycle analysis. The MA3T model, developed by Oak Ridge National Laboratory (ORNL), is a multinomial discrete choice model for projecting the market share of vehicle technologies. One source of data for populating the MA3T model is Autonomie which is a state-of-the-art vehicle system simulation tool used to assess the energy consumption, performance, and cost of multiple advanced vehicle technologies across classes (from light- to heavy-duty), powertrains (from conventional to hybrid electric vehicles [HEVs], plug-in hybrid electric vehicles [PHEVs], battery electric vehicles [BEVs], and fuel cell electric vehicles [FCEVs]), components, and control strategies. VISION, developed by Argonne National Laboratory, is a vehicle stock and GHG emissions projection model that uses GREET which is an analytical tool that simulates the energy use and emissions output of various vehicle and fuel combinations. As shown in Figure III.1.1, the MA3T model projects sales and shares by vehicle type (car, sport utility vehicle [SUV], pickup, etc.) and powertrain technology (gasoline, BEV, PHEV, etc.), and these outputs are used as inputs for the VISION model to calculate the resulting life cycle GHG emissions. For simplicity, the total sales and classifications (passenger cars and light trucks) of LDVs projected in this study are kept as the default values in the VISION model. The development level of plug-in electric vehicle manufacturing cost (battery cost), charging infrastructure, and vehicle energy policies are adjusted in the MA3T model under different scenarios.



Autonomie = Vehicle System Simulation Tool

GREET = Greenhouse gases, Regulated Emissions, and Energy use in Transportation

Figure III.1.1 Modeling framework of the Cumulative Public Recharging model used to calculate life cycle GHG emissions. Source: ORNL

This study [1] projects the impacts of technology and policy enforcement on shaping the dynamics and decarbonization of the LDV market. Achieving the expected improvement of battery technology and charging infrastructure is critical but can reduce the 2050 GHG emissions to only 48%–54% of the 2020 level under the renewable electricity mix scenario. Among the 18 different energy/technology/policy cases, it is found that achieving a 100% BEV stock by 2050—or the 2050 net-zero target in the LDV industry—is almost impossible unless a ban on internal combustion engine technology is implemented starting in 2035 and under the 2035 100% clean electricity scenario. More detailed explanations can refer to [1]. These extreme conditions also call for the most sacrifice, from the consumer welfare perspective. A policy with greater forcing intensity accelerates plug-in electric vehicle penetration but with a declining marginal effect and reduced consumer welfare which is the quantified consumer pay/gain in the vehicle market dynamics. Among the investigated policy scenarios, a policy-forcing intensity equivalent to a fuel tax of $1–$2 per gallon of gasoline reduces the most GHG emissions while keeping positive consumer welfare or demand above the price paid.

Improving the Effectiveness and Equity of Fuel Economy Regulations with Sales Adjustment Factors

Larger vehicles, such as sports utility vehicles, consume more energy than cars [2]. The increasing popularity of these energy-intensive vehicles runs contrary to the goal of stricter vehicle fuel economy regulations to reduce fuel consumption as well as criteria and GHG emissions, but this popularity can be explained by consumer preference and less-stringent regulations for larger vehicle footprints. Current regulations recognize differences among new vehicle models in terms of vehicle efficiency and sales volume but ignore the variation in lifetime vehicle distance traveled among vehicle classes. This study shows that, for both the United States and China, large vehicles travel more, last longer, and are owned by higher-income consumers. Therefore, large vehicles use more fuel and emit more pollutants than represented by current policy, and thus the findings raise both policy effectiveness and energy equity concerns. We propose and estimate the Sales Adjustment Factors that weight fuel economy standards based on vehicle usage and demonstrate the resultant significant improvement in the effectiveness and equity of fuel economy regulations.

BEV Charging Behaviors and Deployment of Public Charging Infrastructure

To reduce system energy consumption by ensuring that BEVs are as usable as conventional vehicles, a certain level of public charging availability is needed. Direct current fast charging (DCFC) faces profitability difficulty and skepticism as to its cost-effectiveness [3], while more expensive extreme fast charging (xFC) is being developed. To inform decisions for charging technology deployment, the potential utilization and deployment priority of different types of charging infrastructures must be better understood. This project has developed a data-driven Cumulative Public Recharging model to explore travel patterns using 2017 National Household Travel Survey data. Given the revealed daily trip sequence, trip distance, dwell times, and assumptions of vehicle recharging behaviors, the study examines the daily maximum charging potentials and the resulting maximum all-electric range under different types of charging speeds, battery capacity, and charging behavior constraints, as shown in Figure III.1.2. The results suggest that (1) more advanced public chargers and high-charging opportunities increase the daily maximum driving range; (2) residential charging is sufficient for most daily short-distance trips, while public chargers are still needed for middle- and long-distance trips; (3) xFC for LDVs may not be necessary for people with home charging but could be more useful for people without and for situations that require urgent charging, and (4) xFC for LDVs becomes even less important with longer BEV ranges. One conclusion is that the high market penetration of Level 2 chargers and the medium market penetration of DCFC should be considered primarily for deployment to serve all short-, mid-, and long-distance trips. The details of this study refer to Li and Lin [4].

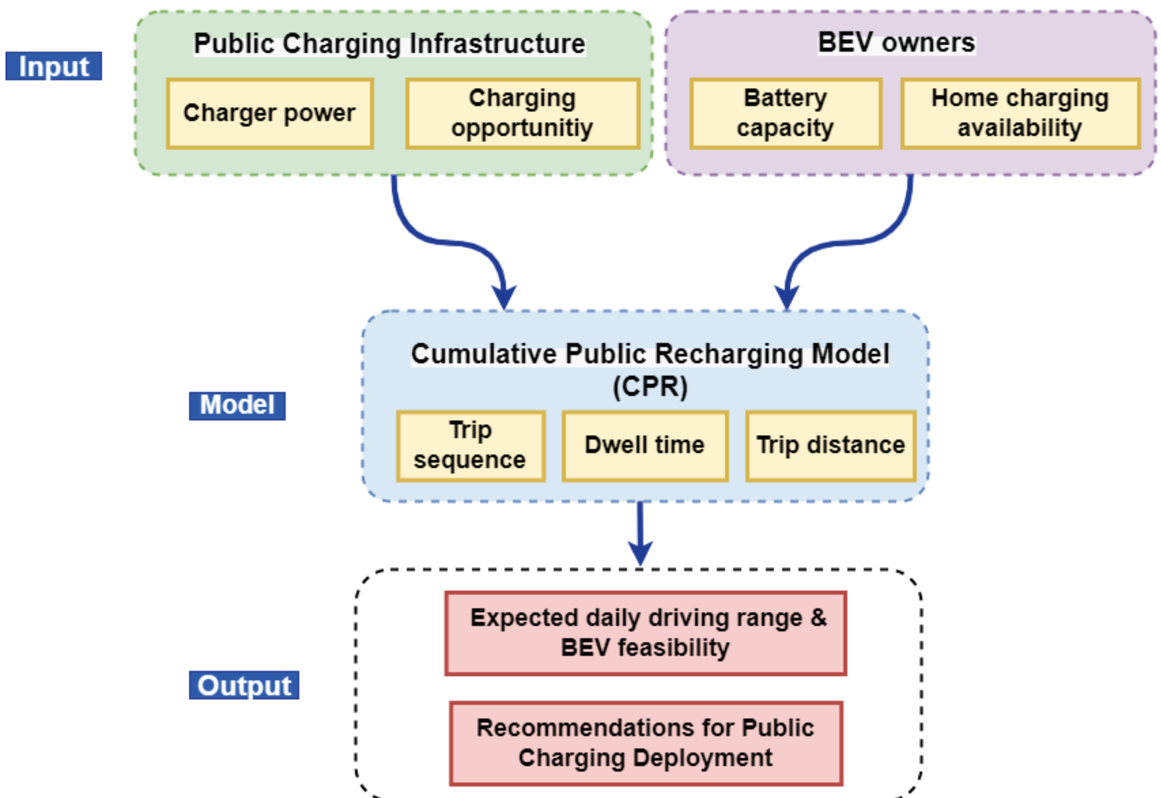


Figure III.1.2 Modeling framework of the Cumulative Public Recharging model used to calculate the expected daily driving range and BEV feasibility as well as recommendations for public charging deployment. Source: ORNL

Nationwide Energy and Mobility Impacts of Electric Air Taxis on Road Traffic

Fuel economy and travel patterns of the on-road vehicles were taken from the National Household Travel Survey, and we used the probabilities to fit the distributions. The air taxi's fuel economy was based on a literature review. Electric air taxis, also known as flying cars, are considered to be the next phase of mobility. They are far smaller and quieter than commercial planes, which allows for vertical takeoff and landing. The goal is to link urban centers (especially congested cities) with suburbs and offer faster and more energy-efficient mobility services than traditional modes, e.g., transit, taxis, and passenger vehicles. The objective of this research is to extend and scale up our previous corridor-level model to quantify the nationwide impact of air taxis on driver travel time and on-road energy use, as shown in Figure III.1.3. The work involves (1) developing a simple cost-benefit model of mode choice by multiple people traveling through the same route during the same hour, with the heterogeneous value of travel time in the context of a given trip origin-destination pair, and (2) calculating the aggregate effect of choices between on-road vehicles and air taxis on the average traffic speed along the origin–destination path, the resulting travel time of travelers, and the energy use of vehicles along the route. We selected the most congested corridor in the 15 most congested U.S. cities for a numerical experiment. The results suggest that incorporating air taxis on interstate highways and local arterials can achieve total energy savings of up to 6.09% and 11.10%, respectively, compared to the traffic networks without air taxis.

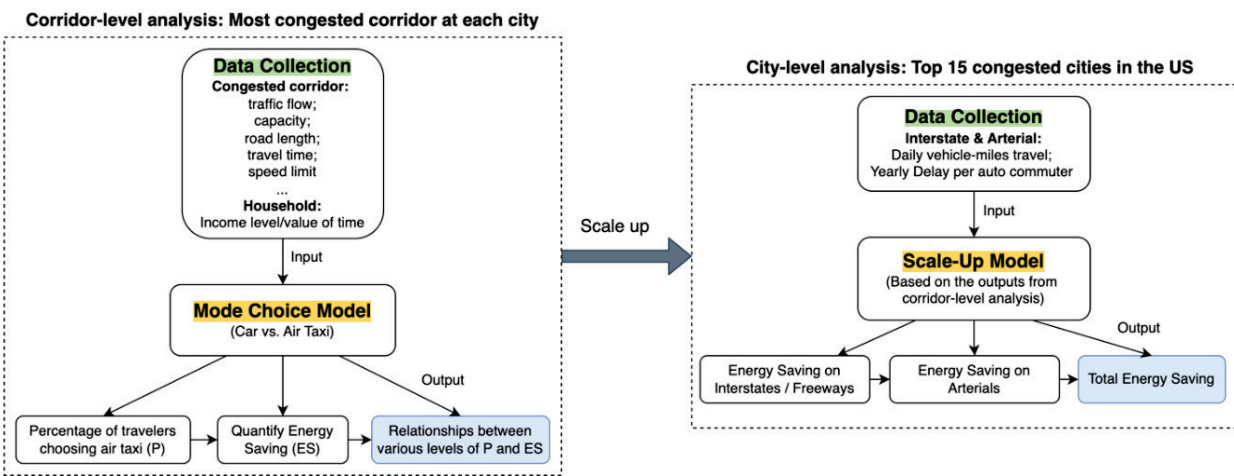


Figure III.1.3 Modeling framework used to extend and scale up the previous corridor-level model and to quantify the nationwide impact of air taxis on driver travel time and on-road energy use. Source: ORNL

Progress on MA3T-Used Model Construction

During FY 2022, the team made progress on creating several components of the MA3T-used model. The first component is the set of scrappage schedules that will be applied to the used vehicle fleet in the MA3T model. These scrappage schedules are based on an econometric analysis published by Greene and Leard [5]. This analysis yields a set of scrap rate schedules by vehicle class (car, sport utility vehicle and van, and pickup truck) for the most recent year of data that can be used to calculate scrap rates, 2003 to 2020, as shown in Figure III.1.4. We apply these scrappage curves to explore the relationship between fleet turnover and GHG from passenger vehicles [6].

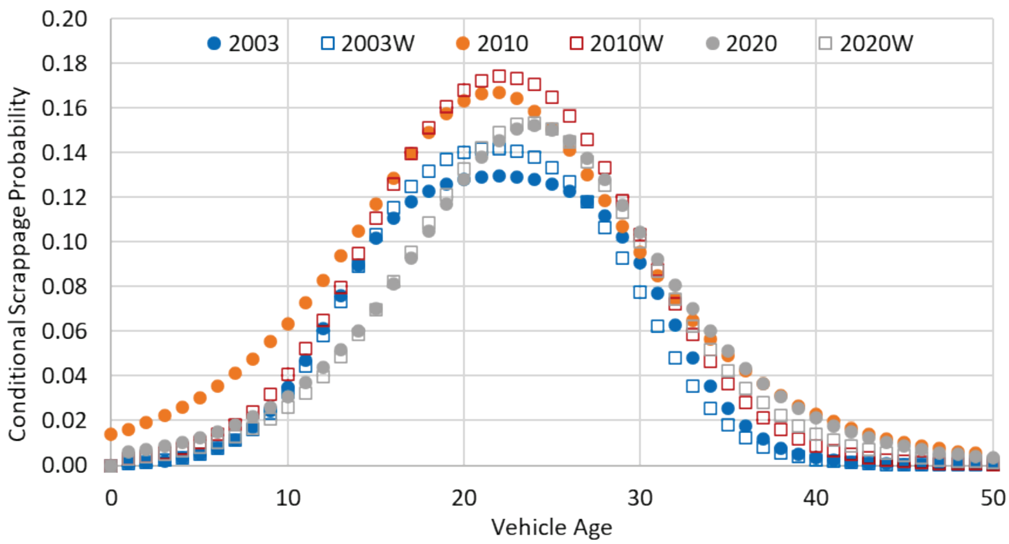


Figure III.1.4 Conditional scrappage probability curves, 2003, 2010, and 2020 (W represents weighted scrappage logistic curves; the weights are proportional to registrations). Source: University of Tennessee

The second component is a merged dataset that includes scrappage and registration data with used vehicle price data from the Consumer Expenditure Survey. These data include survey-based average purchase prices of used vehicles observed from 2002 to 2019, where averages are defined by the year the vehicle was purchased, vehicle model year, vehicle make, and vehicle class (car versus light truck).

In addition, the team made progress toward completing another important component of the MA3T-used vehicle model: defining the degree of substitution between new and used vehicles. This is represented by the "purchase new" versus "purchase used" nesting parameter in the MA3T model. This parameter can be calibrated to match existing estimates of the aggregate new vehicle market elasticity of demand. We have finalized an updated preliminary set of estimates of this elasticity based on a detailed dataset of 2018 household survey responses from the InMoment company (formerly MaritzCX) linked with vehicle attributes from Wards Auto. The preliminary set of elasticity estimates appears in Table III.1.1.

Table III.1.1 New Preliminary Estimates of the Market Price Elasticity of Demand for New Vehicles*

Income Group	Aggregate Elasticity
<55,000	-0.91
55,000–85,000	-0.60
85,000–125,000	-0.41
125,000–200,000	-0.27
>20,000	-0.07
Average	-0.47

**Based on 2018 data from the University of Tennessee*

Conclusions

In FY 2022, the TEEM team conducted research on GHG emission projection, vehicle fuel economy, charging infrastructure, consumer surplus, and used vehicle-related topics that supported improvements of the MA3T model. The team also published studies on GHG emission projection, vehicle fuel economy, and vehicle scrappage analysis. More research is needed to continue the improvement of MA3T and its derivative models (such as the truck choice model and the MA3T-used vehicle model) toward the goal of achieving fully integrated analyses of emerging energy-relevant technologies.

Key Publications

1. Greene, David L., and Benjamin Leard. 2022. *A Statistical Analysis of Trends in Light-duty Vehicle Scrappage and Survival: 2003-2020*. Howard H. Baker Jr. Center for Public Policy. June 28. https://bakercenter.utk.edu/energy-and-environment-reports/a-statistical-analysis-of-trends-in-light-duty-vehicle-scrappage-and-survival-2003-2020/.
2. Leard, Benjamin and David L. Greene. 2022. *Stock Turnover and the Decarbonization of Passenger Vehicles*. Howard H. Baker Jr. Center for Public Policy and University of Tennessee, Knoxville. https://bakercenter.utk.edu/wp-content/uploads/2022/10/Stock-Turnover-and-the-Decarbonization-of-US-Passenger-Vehicles-Report.pdf.
3. Ou, Shiqi, Zhenhong Lin, Yilan Jiang, and Shengyong Zhang. 2022. "Quantifying policy gaps for achieving the net-zero GHG emissions target in the US light-duty vehicle market through electrification." *Journal of Cleaner Production*: 135000.
4. Ou, Shiqi, Zhenhong Lin, Chieh Ross Wang, Stacy Davis, Shasha Jiang, Michael Hilliard, Ho-Ling Hwang, Xu Hao, and Rujie Yu. 2022. "Improving the effectiveness and equity of fuel economy regulations with sales adjustment factors." *iScience* 25, no. 9: 104902.

References

1. Ou, Shiqi, Zhenhong Lin, Yilan Jiang, and Shengyong Zhang. 2022. "Quantifying policy gaps for achieving the net-zero GHG emissions target in the US light-duty vehicle market through electrification." *Journal of Cleaner Production*: 135000.
2. Ou, Shiqi, Zhenhong Lin, Chieh Ross Wang, Stacy Davis, Shasha Jiang, Michael Hilliard, Ho-Ling Hwang, Xu Hao, and Rujie Yu. 2022. "Improving the effectiveness and equity of fuel economy regulations with sales adjustment factors." *iScience* 25, no. 9: 104902.
3. Schroeder, Andreas, and Thure Traber. "The economics of fast charging infrastructure for electric vehicles." *Energy Policy* 43 (2012): 136-144.
4. Li, W., and Z. Lin. 2022. "Deployment Priority of Public Charging Speeds for Increasing Battery Electric Vehicle Usability – Insights from Revealed Travel Patterns." In *Proceedings of the 100th Annual Meeting of Transportation Research Board*, Washington, DC.
5. Greene, David L., and Benjamin Leard. 2022. "A Statistical Analysis of Trends in Light-duty Vehicle Scrappage and Survival: 2003-2020." Howard H. Baker Jr. Center for Public Policy. June 28. https://bakercenter.utk.edu/energy-and-environment-reports/a-statistical-analysis-of-trends-in-light-duty-vehicle-scrappage-and-survival-2003-2020/.
6. Benjamin Leard, and Greene, David L. 2022. *Stock Turnover and the Decarbonization of Passenger Vehicles*. Howard H. Baker Jr. Center for Public Policy and University of Tennessee, Knoxville. https://bakercenter.utk.edu/wp-content/uploads/2022/10/Stock-Turnover-and-the-Decarbonization-of-US-Passenger-Vehicles-Report.pdf

Acknowledgments

Other project team members are David Greene, Zulqarnain Khattak, Mingzhou Jin, Ben Leard, Zhenhong Lin, Wan Li, Nawei Liu, and Fei Xie.

III.2 Medium- and Heavy-Duty Vehicle Choice Modeling and Applied Analysis (National Renewable Energy Laboratory)

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Start Date: October 1, 2021 End Date: September 30, 2022
Project Funding: $300,000 DOE share: $300,000 Non-DOE share: $0

Project Introduction

The U.S. Department of Energy's Vehicle Technologies Office (VTO) and Hydrogen and Fuel Cell Technologies Office (HFTO) support research and development of efficient, affordable, and sustainable transportation technologies. These efforts support the Office of Energy Efficiency and Renewable Energy's programmatic priority to decarbonize the national transportation system across all modes: air, sea, rail, and road. VTO and HFTO programs include research on batteries, electric drive technologies, combustion, energy efficient mobility systems, materials, fuel cells, and hydrogen storage. This project focuses on analyzing pathways to decarbonize the medium- and heavy-duty (MDHD) on-road sector by leveraging prospective advancement of the technologies supported by VTO and HFTO.

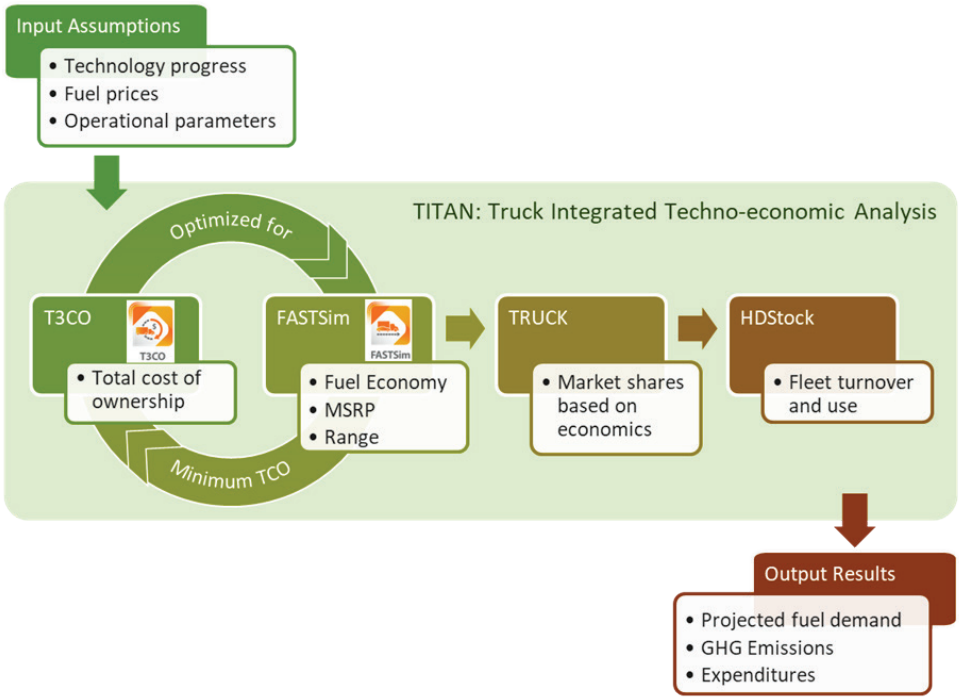
Objectives

The project objective is to assess the energy and emissions benefits from achieving technology progress assumptions within alternative policy and market contexts conducive to decarbonizing the transportation sector.

Approach

This analysis evaluates the benefits of technology improvements in the U.S. MDHD vehicle fleet based on adoption of technologies that enter the market between 2025 and 2050. While the analysis does not assess outcomes after 2050, the trends suggest that energy and emissions reductions will continue to grow with significant benefits after that date. Two parallel analysis methodologies were pursued using (1) the National Renewable Energy Laboratory (NREL) Truck Integrated Techno-economic Analysis (TITAN) suite of modeling tools applied to vehicles in Class 4–8 and (2) the MDHD Automotive Deployment Options Projection Tool (MDHD ADOPT) applied to the Class 8 tractor–trailer market. Both approaches capture consumer heterogeneity through the distribution of annual vehicle miles traveled.

As shown in Figure III.2.1, TITAN includes the Transportation Technology Total Cost of Ownership (T3CO) model, the Future Automotive Systems Technology Simulator (FASTSim) vehicle powertrain model [1], the TRUCK payback-based adoption model, and the HDStock vehicle stock model. T3CO, integrated with FASTSim, selects and sizes component technologies to meet performance requirements while minimizing total cost of ownership (TCO). TRUCK and HDStock are then exercised sequentially. This complete workflow translates component- and vehicle-level goals into future in-use fleet energy consumption and emissions.



MSRP = manufacturer's suggested retail price GHG = greenhouse gas TRUCK = name of the model

Figure III.2.1 TITAN Modeling Framework. Source: National Renewable Energy Laboratory (NREL)

MDHD ADOPT is a fully integrated vehicle simulation (also leveraging FASTSim), vehicle choice, and stock model that estimates vehicle technology improvement impacts on sales, energy, and emissions [2]. The model includes all existing vehicle options for realism, estimates their sales using consumer preferences, creates new market-driven vehicle options based on market success, and rolls up sales to estimate energy and emissions.

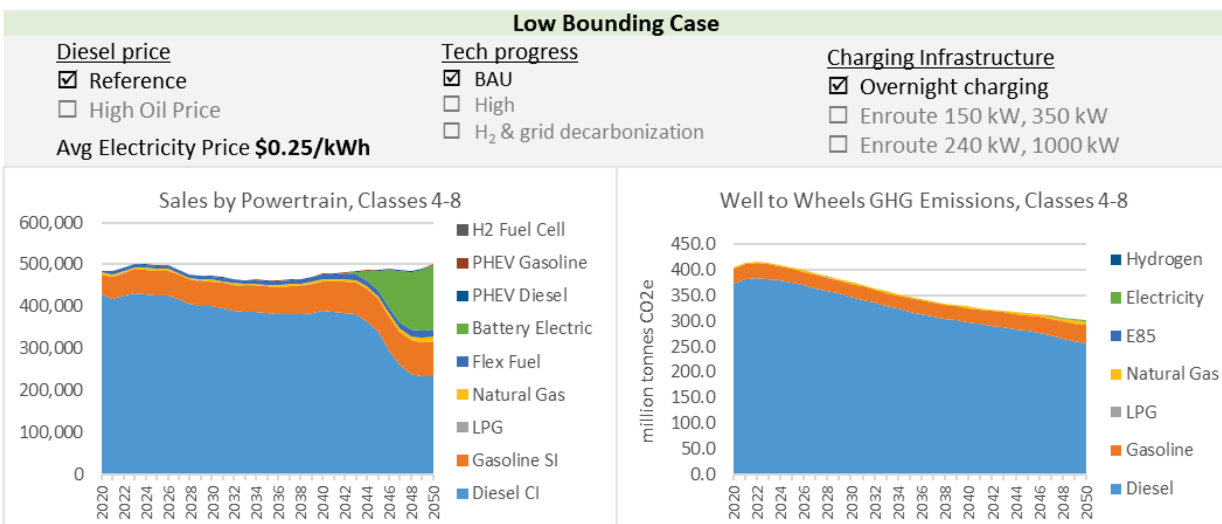
Assumed technology improvement trajectories feed into both modeling tools and are applied to the vehicles through time. These trajectories are represented by a business-as-usual (BAU) scenario, which reflects technology improvements consistent with historic advancement, and a high-technology-improvement scenario, under which VTO and HFTO program goals and objectives are realized. These assumptions include outcomes and goals of past and ongoing VTO and HFTO investments and partnerships, including the SuperTruck initiative, the 21st Century Truck Partnership, and published HFTO targets for Class 8 long-haul tractors [3]. This includes performance and cost goals or expected potential for diesel engine efficiency, long-haul tractor freight efficiency, aerodynamic drag, batteries, motors, and fuel cells. Using FASTSim, these assumptions determine future vehicle characteristics, fuel economy, and cost for hybrid diesel–electric (HEV), battery electric (BEV), fuel cell electric (FCEV), and conventional powertrains. In the TITAN approach, a single BEV range goal is specified for each vehicle model as a constraint for T3CO optimization. Meanwhile, MDHD ADOPT endogenously determines BEV range based on sales success, resulting in multiple options that meet the heterogenous requirements of the market. For both approaches, a 1.5 cost multiplier is used to convert assumed component manufacturing costs to consumer price. The team plans to publish a report on the latest analysis in Fiscal Year 2023, which will include the detailed technology improvement assumptions used. For further reference, the full report on the previous iteration of the analysis is listed in the Key Publications section below.

Results

TITAN Results

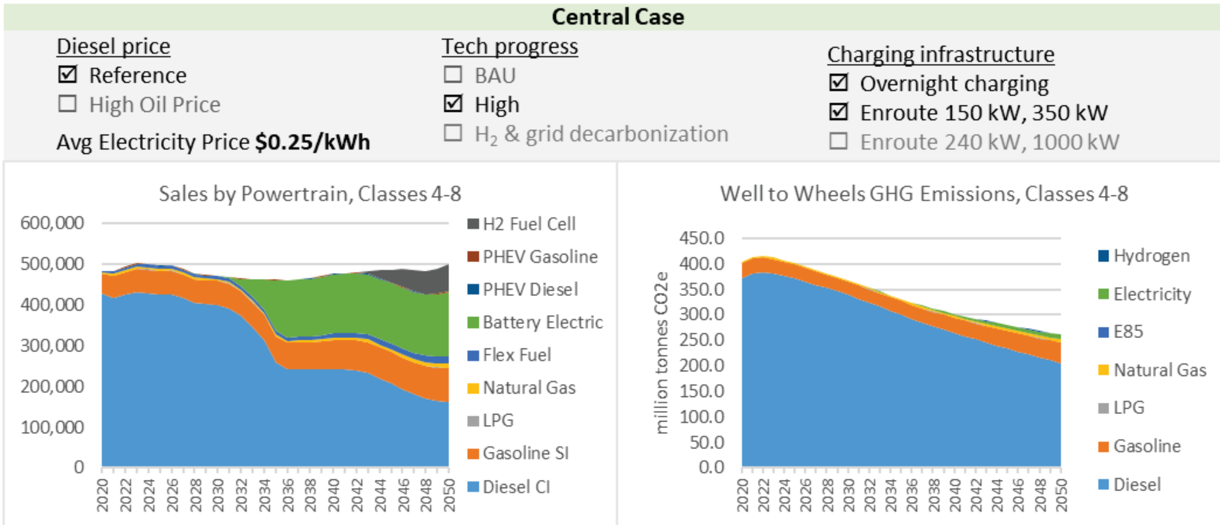
More than 100 scenarios were analyzed in TITAN, including combinations of the two technology progress trajectories, two diesel price scenarios from the Annual Energy Outlook (AEO) 2022 Reference and High Oil Price (HOP) cases [4], 11 electricity price sensitivities averaging from $0.12/kWh to $0.36/kWh, and three assumptions regarding BEV charging. With an assumption of overnight charging only, BEV adoption is limited to segments in which the average daily mileage is less than or equal to the vehicle's range. This assumes that adoption occurs when vehicles can complete their average daily missions without stopping to charge. In the second and third cases, these limits were removed such that BEV adoption may occur whenever the vehicle payback is acceptable. However, a penalty of $75/hour applies to the time required to charge enroute to make up the daily range deficiency. These scenarios explore two charging powers: 1) 150 kW for vocational trucks and 350 kW for tractors, and 2) 240 kW for vocational trucks and 1,000 kW for tractors. Vehicle incentives consistent with the Inflation Reduction Act were included in all scenarios. Potential impact of the Inflation Reduction Act on fuel prices was not included. It should be noted that gasoline, flex fuel, propane, natural gas, and plug-in hybrid powertrains were not analyzed. The sales of these vehicles were held constant at the AEO 2022 Reference Case values.

Three scenarios are highlighted below. The low case shown in Figure III.2.2 presents a BAU trajectory in terms of diesel price and technology progress, with range limits representing a national charging infrastructure that lags adoption such that trucks must charge overnight. Penetration of zero-tailpipe-emission vehicles (ZEVs) begins in 2040 but only in vocational (non-tractor) trucks. The central case shown in Figure III.2.3 differs from the low case in the technology progress rate and a charging network sufficient to enable completion of all daily missions. Decarbonization starts earlier, with 100% ZEV adoption in Class 4–6 trucks and 60% in Class 7–8 vocational trucks by 2050. Tractors remain nearly 100% reliant on diesel.



** HEVs are included with diesels. Sales of gasoline, flex fuel, natural gas, propane (liquefied petroleum gas [LPG]), and plug-in hybrid electric vehicles (PHEVs) are from the AEO 2022 Reference Case. GHG = greenhouse gas; SI – spark ignition; CI = compression ignition; CO2e = carbon dioxide equivalent; E85 refers to a fuel blend of 85% ethanol fuel and 15% gasoline or other hydrocarbon by volume.*

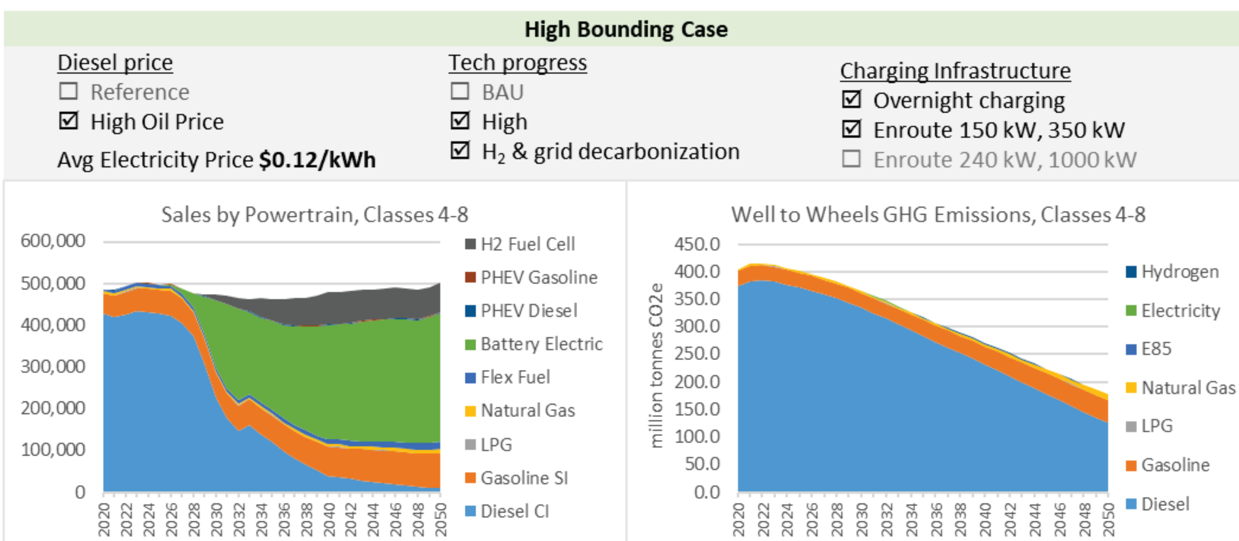
Figure III.2.2 TITAN low scenario results. Source: NREL



** HEVs are included with diesels. Sales of gasoline, flex fuel, natural gas, LPG, and PHEVs are from the AEO 2022 Reference Case.*

Figure III.2.3 TITAN central scenario results. Source: NREL

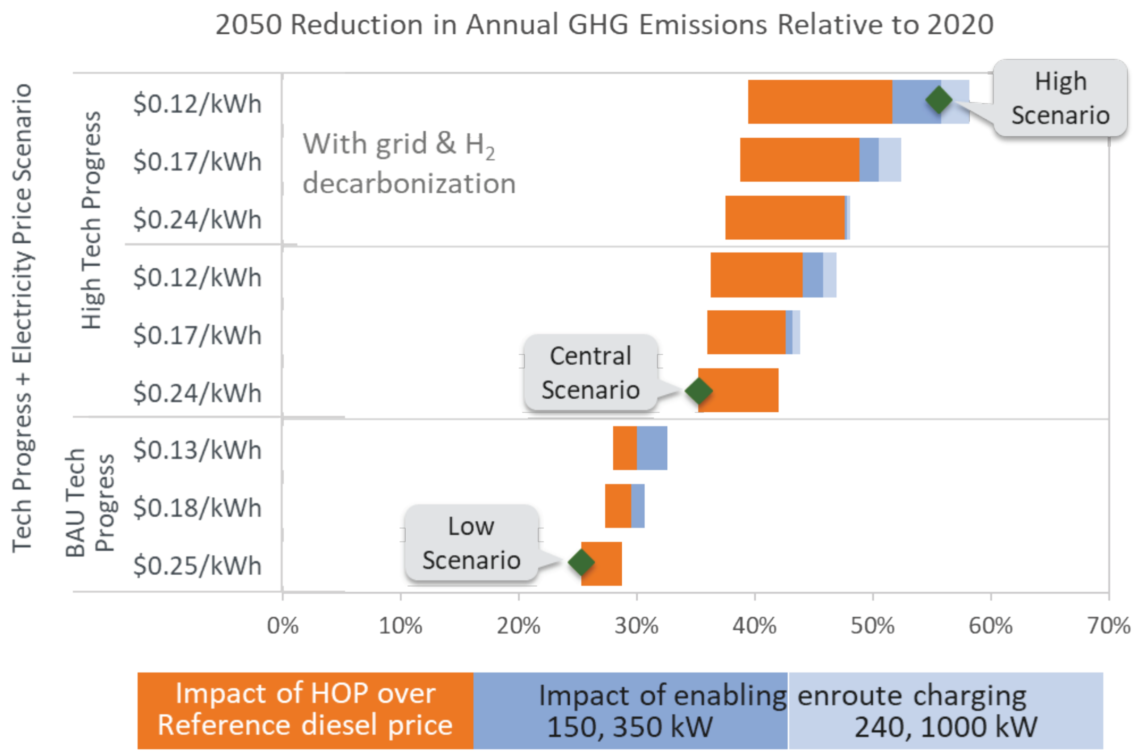
The high bounding case shown in Figure III.2.4 incorporates a high diesel price, a low electricity price, high technology progress, and a charging network sufficient to enable completion of all daily missions. This scenario achieves 95% ZEV adoption in the analyzed classes, with about 7% of sleeper tractors continuing to be purchased as diesel trucks. Adding faster charging accelerates decarbonization, but megawatt-level charging is likely to entail higher electricity price and 2050 ZEV shares are very similar. These scenarios illustrate the importance of market conditions, specifically fuel prices and infrastructure, in future technology success, even with a high rate of technology advancement.



HEVs are included with diesels. Sales of gasoline, flex fuel, natural gas, LPG, and PHEVs are from the AEO 2022 Reference Case.

Figure III.2.4 TITAN high scenario results. Source: NREL

Figure III.2.5 summarizes results from a wider set of scenarios in terms of total in-use fleet annual GHG emissions reductions in 2050 relative to 2020 for the Class 4–8 diesel market. The five highest electricity price scenarios are excluded because BEV adoption is generally very low and late in the analysis horizon for prices above the central case assumption, which averages around $0.24/kWh from 2020 to 2050. For the Reference Case diesel price, technology adoption and emissions reductions are very similar under the two technology trajectories until the electricity price drops below $0.17/kWh. However, decarbonization benefits are significantly higher under the high technology progress case as the electricity price falls to $0.12/kWh. The impact of the HOP is significantly larger under the high technology progress case. Meanwhile, the addition of en-route charging on top of a higher diesel price has relatively more impact under the BAU technology progress case. Decarbonization of the electricity grid and hydrogen (H_2) production further enhances the emissions benefits. Fleetwide ZEV adoption by 2050 ranges from 64% to 95% of the analyzed classes, while annual GHG emissions reductions in 2050 relative to 2020 range from 25% to 60%. As these results show, even the high bounding case would require net-zero-carbon drop-in fuels to fully decarbonize the in-use fleet by 2050, owing to the time required for the vehicle stock to turn over.

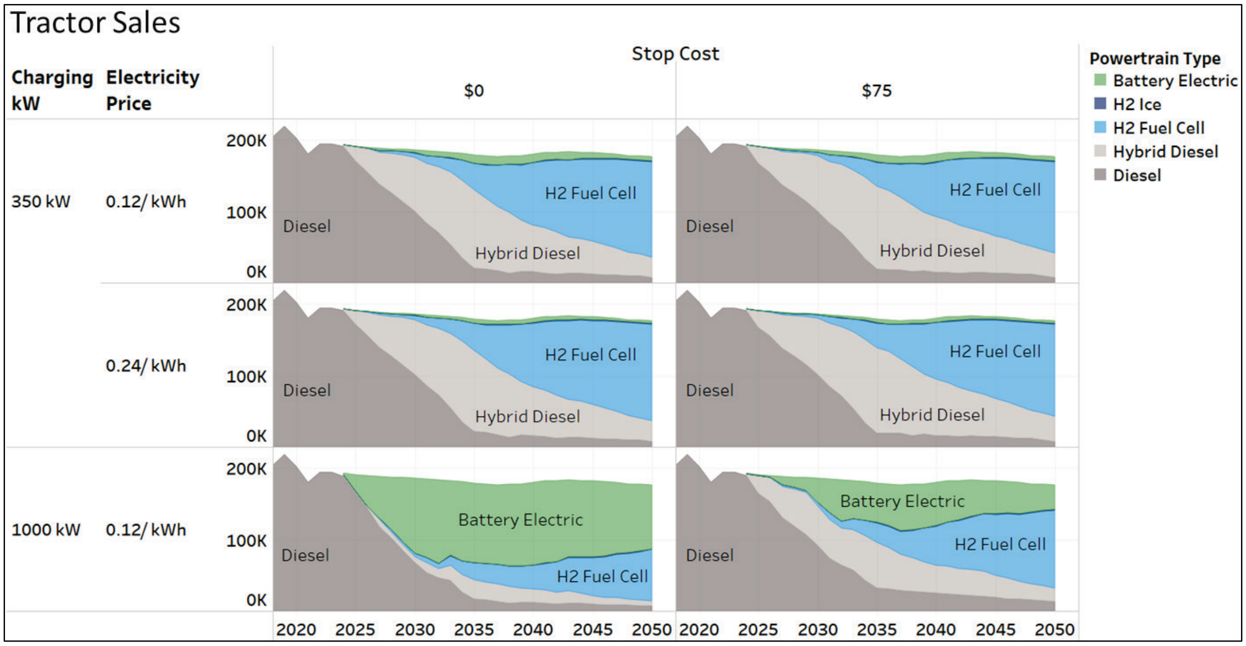


Electricity price varies over the projection period for each scenario and differs between the AEO Reference and HOP cases. Rough averages are provided here for comparison purposes.

Figure III.2.5 TITAN scenario analysis summary. Source: NREL

MDHD ADOPT Results

A select set of six scenarios was analyzed in parallel using MDHD ADOPT, as illustrated in Figure III.2.6. These scenarios represent high technology progress under the HOP diesel price, two electricity prices, two charging powers (350 kW and 1,000 kW), and two fueling stop cost assumptions. These assumptions are established independently—i.e., the electricity price is not dependent on charging power. In MDHD ADOPT, consumer adoption depends not only on vehicle and fuel costs but also on consumer preferences for vehicle attributes, including power and vehicle range. The value of vehicle range consists of two components representing the disutility of refueling frequency (stop cost) and dwell time. All powertrains incur this range penalty, but BEVs are allowed one stop per day for free, representing the ability to recharge at home base at the end of the day.



All scenarios assume high technology progress and HOP. ICE = internal combustion engine

Figure III.2.6 MDHD ADOPT scenario results, tractor sales. Source: NREL

The MDHD ADOPT results are generally similar to the TITAN results, showing that high technology progress and high diesel price enable ZEV adoption, but low electricity price and fast charging infrastructure are also necessary to enable BEV adoption in the tractor market. BEV adoption generally displaces FCEVs but does expand the total ZEV market and is necessary to approach the 100% ZEV goal. This market growth is larger when the penalty for charge frequency is removed.

As expected, BEV sales are higher for market segments with lower vehicle miles traveled and daily range requirements. MDHD ADOPT endogenously creates BEVs with a variety of battery sizes that are adopted at varying rates by consumers in each segment. Figure III.2.7 illustrates the difference in sales-weighted average range for each consumer segment and the impact of the two range penalty components. In each charging power scenario, BEV range is initially about the same. Over time, average BEV range increases as battery costs decline, with higher penalties per charging event resulting in higher BEV range in 2050. While higher charging power might be expected to result in the need for smaller batteries, the initial average BEV range is actually higher. This result likely arises from the decrease in recharging time (from 50–90 minutes at 350 kW to 17–34 minutes at 1,000 kW) and the overall improved attractiveness of the BEV. When stop costs are high, this differential disappears over time, and the 2050 average BEV range is very similar under the two charge power scenarios.

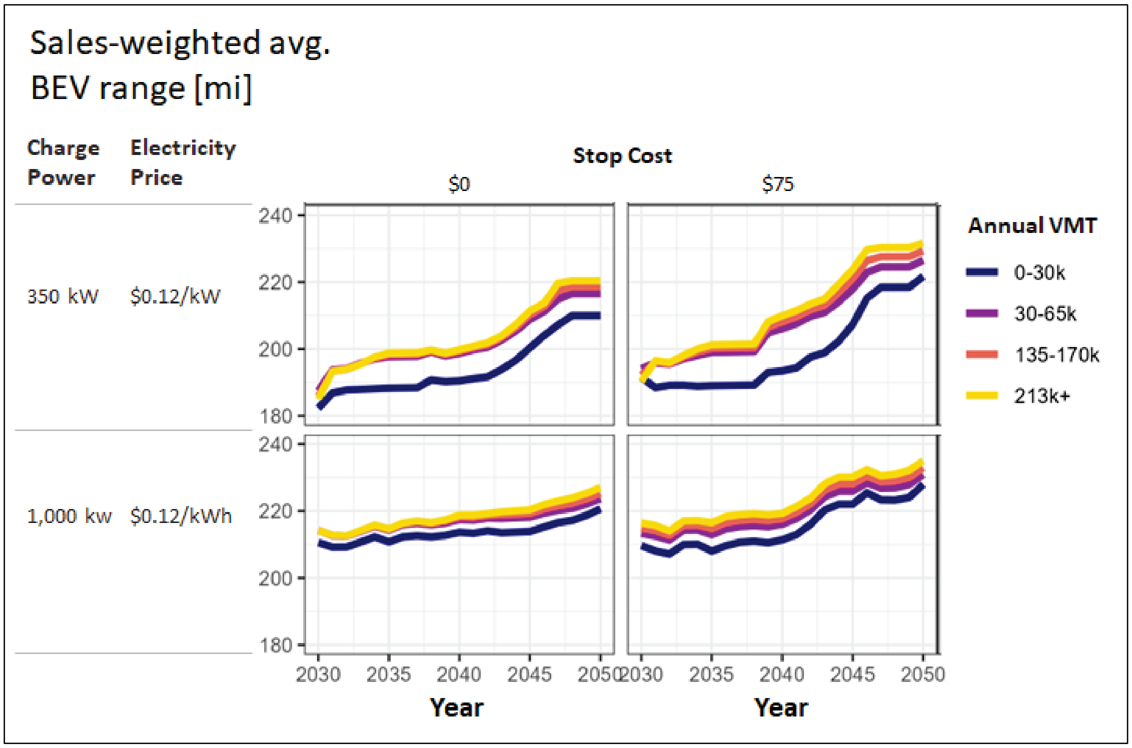


Figure III.2.7 MDHD ADOPT sales-weighted average BEV range (miles) by vehicle miles traveled bin. Source: NREL

Conclusions

This analysis examined technology progress under a range of market conditions and identified decarbonization pathways for MDHD vehicles. The results indicate that achieving 100% ZEV sales by 2050 requires a combination of high technology progress, high diesel price, low electricity price, and charging infrastructure sufficient to eliminate range limitations. ZEV uptake begins first in vocational trucks under all scenarios. Sleeper cab tractors are last to decarbonize because of high energy and range requirements that result in large batteries and higher incremental cost. Owing to lags in stock turnover, the high bounding case would still require net-zero-carbon drop-in fuels to fully decarbonize the in-use fleet by 2050.

This project also demonstrated new commercial vehicle market analysis capabilities provided by MDHD ADOPT, including valuation of the wider variety in performance attributes that is enabled by new powertrain options. MDHD ADOPT endogenously determines BEV and FCEV range for different market segments, trading off added mass and cost with decreased refueling time and frequency.

Key Publications

1. Brooker, Aaron, Alicia Birky, Evan Reznicek, Jeff Gonder, Chad Hunter, Jason Lustbader, Chen Zhang, Lauren Sittler, Arthur Yip, Fan Yang, and Dong-Yeon Lee. 2021. *Vehicle Technologies and Hydrogen and Fuel Cell Technologies Research and Development Programs Benefits Assessment Report for 2020*. National Renewable Energy Laboratory, NREL/TP-5400-79617. www.nrel.gov/docs/fy21osti/79617.pdf.

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2. Brooker, A., J. Gonder, S. Lopp, and J. Ward. 2015. “ADOPT: A Historically Validated Light Duty Vehicle Consumer Choice Model.” SAE Technical Paper 2015-01-0974. https://www.sae.org/publications/technical-papers/content/2015-01-0974/.

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III.3 Electric Vehicle Infrastructure for Equity (EVI-Equity) (National Renewable Energy Laboratory)

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Start Date: June 1, 2021 End Date: June 30, 2022
Project Funding: $200,000 DOE share: $200,000 Non-DOE share: $0

Project Introduction

Traditional plug-in electric vehicle (PEV) charging infrastructure analysis has primarily focused on estimating potential charging demand, with typical main goals of assessing adequate capacity of charging infrastructure (e.g., the number of charging ports) and the potential burden (e.g., electrical load) on or interaction with the electric grid. However, such an approach tends to neglect the equity dimension of infrastructure planning, as the focus is put on matching supply and demand, where demand is mostly driven by a small cohort of people (e.g., mainstream PEV consumers, primarily high-income earners).

From an equity standpoint, beyond the mainstream demand or supply, it is crucial to ensure that all individuals and households benefit from PEV technology. To that end, it is important to get a better understanding of who is benefiting (or not) from PEV technology or charging infrastructure, as well as the barriers that disadvantaged, underrepresented, or underserved communities may have to receiving the same benefits.

Modeling and analysis of equitable PEV adoption and corresponding electric vehicle supply equipment (EVSE) infrastructure requires a comprehensive and detailed model/tool, which is currently lacking.

Objectives

The main objective of this project by the National Renewable Energy Laboratory (NREL) is to support the VTO Analysis program with detailed information as to the inequity (if any) of the current and future deployment of electric vehicles and charging infrastructure. Equity involves both practice (e.g., community engagement) and tools (e.g., data analysis), and this project is more focused on the latter. More specifically, this project aims to develop a sophisticated analysis tool that has sufficiently high spatial resolution, while being scalable from neighborhoods (e.g., census block groups [CBG]) to cities, states, and the nation.

The project quantifies and investigates equitable access to and distribution of existing and future deployment of PEVs and EVSEs in neighborhoods, cities, states, and the nation. When doing so, the project considers electric vehicle adoption and charging infrastructure simultaneously in an integrated manner for more accurate assessment of the dynamic between the two. The project also incorporates broader environmental justice, energy justice, and energy equity principles, frameworks, methods, and data. This project aims to help provide critical information for the transition toward more just and equitable vehicle electrification.

Approach

The project developed the Electric Vehicle Infrastructure for Equity (EVI-Equity) model [1] to evaluate equity implications of current and future deployment of PEVs and EVSEs across the country on a CBG level. EVI-Equity examines the relationship between PEVs/EVSEs and individual households in each CBG. The basic building block of EVI-Equity is synthetic households that contain household-level integrated information associated with socio-demographics and economics (e.g., income, race, ethnicity), housing (e.g., residence type, parking options), transportation (e.g., vehicle ownership, distance traveled), and environment (e.g., air pollution).

As shown in Figure III.3.1, despite some overlap, EVI-Equity is not a vehicle choice model (e.g., the Automotive Deployment Options Projection Tool [ADOPT] [2]), PEV charging simulation tool (e.g., Electric Vehicle Infrastructure – Projection [EVI-Pro] [3]), or travel demand model such as NREL's research on travel demand modeling and analysis [4]. It is a crosscutting and multidisciplinary analysis tool, dedicated to evaluating equitable PEV adoption and EVSE deployment, encompassing and bridging a wide variety of related tools, models, and frameworks.

EVI-Equity takes two types of inputs: historical distribution of EVSEs (e.g., the Alternative Fuels Data Center [AFDC] [5]) or PEVs (e.g., vehicle registration data), as well as custom input (predefined distribution or total number of PEVs/EVSEs). The model then generates equity metrics (e.g., access, affordability) for the distribution (historical or user-defined) of PEVs and EVSEs, as well as alternative distribution, to improve equity.

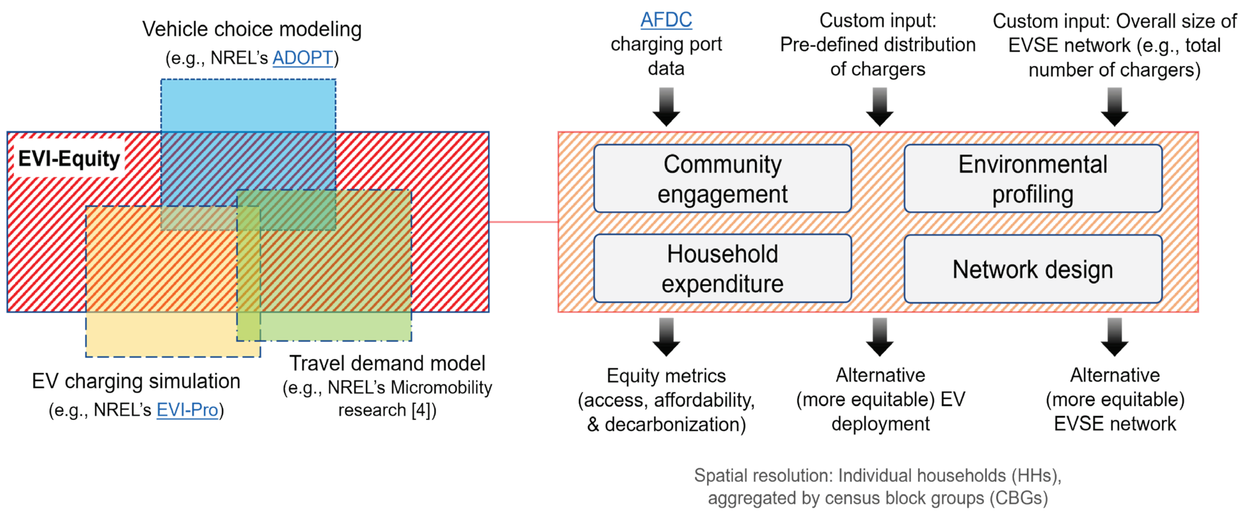

Figure III.3.1 **Input and output of EVI-Equity. Source: NREL**

Results

One of the equity aspects evaluated is the importance of the used vehicle market for lower-income individuals/households. According to the public survey conducted as part of this project, as illustrated in Figure III.3.2, the lower the income, the more likely the respondent is to rely on the used vehicle market. This highlights a need to improve availability and affordability of used electric vehicles for lower-income consumers. Also of note is that the relative reliance on the new vs. used vehicle market may vary with technology as can be seen by contrasting the charts in Figure III.3.2. Possible contributing factors here may include concerns regarding reliability or lack of understanding of PEV technology in general.

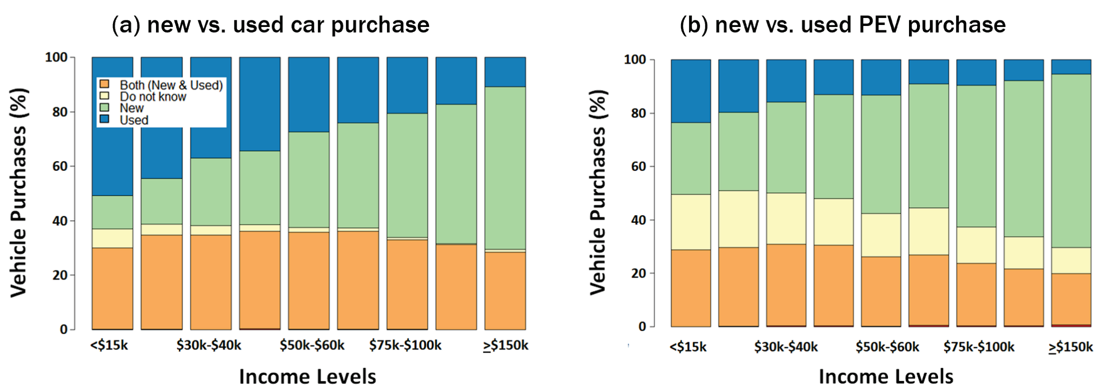

Figure III.3.2 Public survey results for (a) new vs. used car purchase and (b) new vs. used PEV purchase. Source: NREL

The second equity aspect assessed is the potential disparity of hazardous environmental conditions between those who own PEVs and those who do not. For this environmental profiling analysis, a wide variety of environmental factors were examined. As an example, Figure III.3.3 shows the relationship between the spatial distribution of PEVs and ground-level ozone [6] in Atlanta, GA. PEVs are mostly concentrated in or north of downtown, while the concentration of ground-level ozone shows a radial dispersion with downtown at the center. This means that PEV owners in the Atlanta area do not have an advantage in terms of the concentration of ground-level ozone. Statewide comparison between the distribution of PEV owners and ground-level ozone also reveals that only 20% of PEV owners in Georgia (mostly away from the downtown Atlanta area) live in an area with relatively better air quality (with respect to ground-level ozone). In comparison, 65% of PEV owners in California live in an area with relatively better air quality. Figure III.3.3 shows why location matters when it comes to the disparity in hazardous environmental conditions for those who own PEVs vs. those who do not.

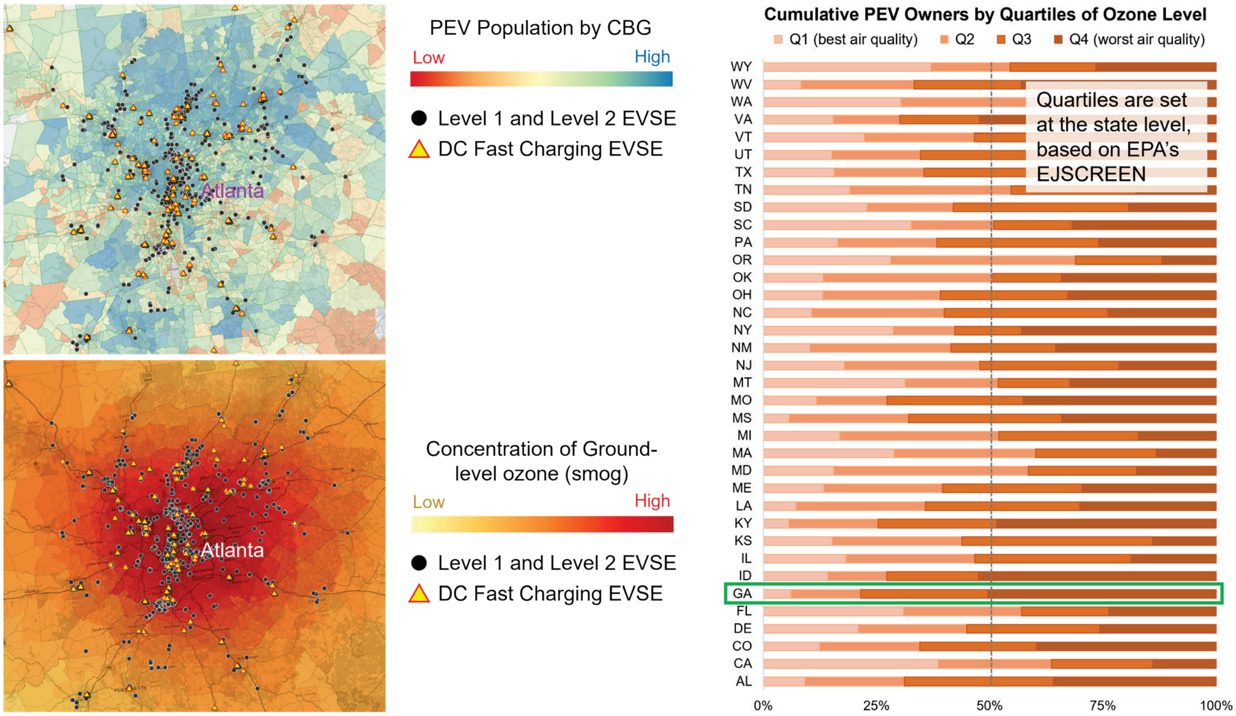

Figure III.3.3 Environmental profiling analysis—ground-level ozone example. Source: NREL

The third equity aspect explored is the affordability of PEVs for different types of households. Figure III.3.4 shows an example for the Denver metro area and the state of South Dakota. For this example, the focus is on the impact of home charging access. The ability to refuel/charge at home is one of the most significant benefits of electric vehicles (compared to their conventional petroleum counterparts). However, not everyone has home charging access, raising equity concerns. Figure III.3.4 implies that not having home charging access, and thus relying on public charging, can increase electricity fuel cost significantly. The increased electricity fuel cost burden on household expenditures, due to the lack of home charging access, affects lower-income households even more. For example, in the Denver metro area, for high-income households, electricity fuel cost accounts for 0.3% with home charging access and 0.4%–1.1% (33%–366% greater) without. For low-income counterparts, the cost is approximately three times greater comparatively—1.1% with home charging access vs. 1.3%–3.5% without. At the extreme, low-income households without home charging access pay approximately between four times (4X) and eleven times (11X) as much for electricity fuel cost than high-income households with home charging access, highlighting the significance of the equity gap. A significant cost to charge a PEV for low-income households might offset the powertrain efficiency of an EV further slowing adoption for low-income communities. Total cost of ownership might not be competitive with a conventional vehicle in these cases.

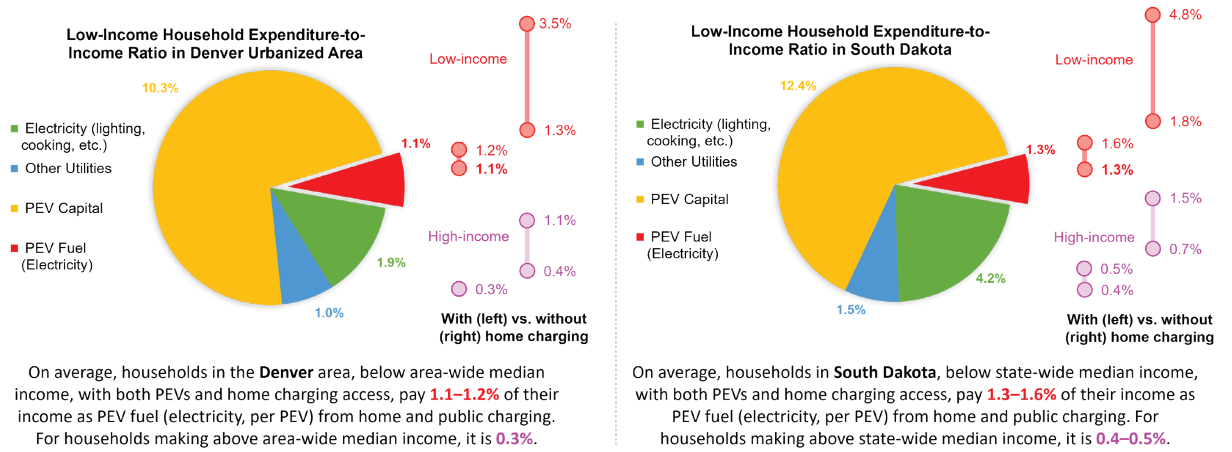

Figure III.3.4 Home charging access and household expenditures for Denver, CO and South Dakota. Percentages represent the ratio of the expenditure items divided by the income Source: NREL

The last equity aspect examined is access to public EVSE. As shown in Figure III.3.5, it is estimated that a little more than 5,000 households currently have access to public EVSE in the Denver metro area, the majority of whom live in relatively wealthy areas (i.e., wealthy CBGs). For the alternative scenario analysis, when the number of public EVSEs in low-income CBGs in the Denver metro area is increased by 50% (of the baseline/existing), with everything else kept the same, the total number of households who have access to public EVSE increases to 6,000. However, the increased access seems to benefit mostly those living in relatively wealthy CBGs. The level of access to public EVSE for those living in low-income CBGs increases significantly only when both EVSEs and PEVs are increased in those disadvantaged areas. In other words, the coordination between PEV adoption and EVSE deployment is crucial to improving access to both PEVs and (public) EVSEs.

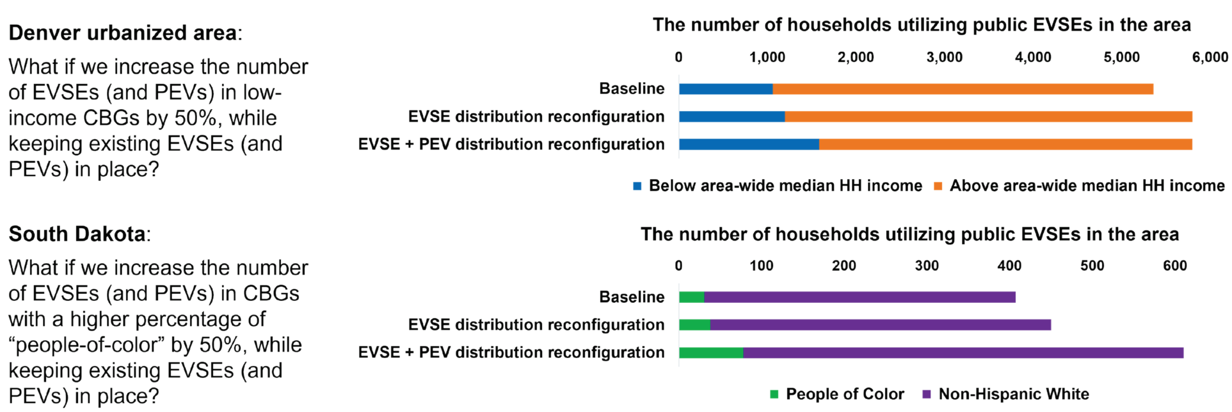

Figure III.3.5 The number of households utilizing public EVSEs in the Denver metro area (top) and South Dakota (bottom). Source: NREL

In the case of South Dakota, access is evaluated in terms of "people of color" vs. non-Hispanic white—more specifically, their population share of EVSEs on a CBG level. For access to existing public EVSE (baseline scenario), the disparity between the CBGs that are predominantly white vs. those that have a greater share of people of color is evident. As an alternative scenario, when the number of public EVSE in CBGs that are predominantly people of color is increased by 50% (while everything else is kept the same), the improved access seems to benefit almost entirely non-Hispanic white households (whether they are located in areas that are predominantly white or people of color). When both EVSE and PEVs are increased in CBGs with a higher percentage of people of color, almost twice the number of households living in minority areas enjoy improved access. This illustrates that coordinating EVSE deployment and PEV adoption can lead to better (distributional) equity outcomes.

Conclusions

This project created a simulation model (EVI-Equity) that can evaluate equitable access to PEVs and EVSE based on individual households in each CBG in the United States, accounting for household-level travel patterns, charging needs, refueling behavior, and other factors. The EVI-Equity model was applied to local, state-by-state, and national analyses of equitable deployment of PEVs and EVSE. In doing so, the project team conducted a large-scale survey (22,000 respondents across the country) to examine public perception, preferences, and behaviors related to alternative transportation modes, perceived barriers to and benefits of electrification, housing types, parking options, power outlet availability, home charging access, vehicle purchase, vehicle utilization, and refueling behavior and preferences. The survey results provided one of the key input data sets for EVI-Equity. The project also examined a wide variety of environmental factors (e.g., air pollution, crime rate) to identify the characteristics of disadvantaged, underrepresented, and underserved neighborhoods. Detailed household expenditures were investigated, accounting for what PEV adoption means for different households in terms of their overall income and expenditures, given the key role of home, workplace, and public charging access. In addition, the project evaluated alternative (more equitable) charging station network design strategies and corresponding impacts (e.g., how many disadvantaged households are benefitting and how much).

EVI-Equity is currently focused on distributional equity ("equitable access to all"). In the future, the model can be refined and expanded in numerous ways. First, other important equity aspects/dimensions (e.g., economics of charging infrastructure) could be considered. Second, NREL's EVI-Pro (daily short-distance) [3], EVI-RoadTrip (long-distance road trips) [7], and EVI-OnDemand (ride-hailing) could be leveraged for a more comprehensive and accurate EV charging infrastructure analysis for future years. Third, the scope could be expanded beyond light-duty vehicles, including medium- and heavy-duty vehicles (e.g., electric paratransit vehicles, school buses, transit buses). Fourth, creating an interactive online platform will be useful so that users can evaluate equitable distribution of PEVs and EVSE in their target geographical areas and download the underlying data and simulation results. Lastly, more holistic (i.e., system-of-systems) equity analysis could be conducted by integrating EVI-Equity with buildings and/or electric grid simulation tools/models.

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III.4 Agent-Based, Bottom-Up Medium- and Heavy-duty Electric Vehicle Economics, Operation, Charging, and Adoption (Colorado State University)

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Start Date: October 1, 2021 End Date: December 31, 2024
Project Funding: $325,032 DOE share: $292,541 Non-DOE share: $32,491

Project Introduction

The national transportation system faces pressing sustainability challenges, including the need to reduce the environmental impacts of transport, while acknowledging the increasingly important role of transport in the U.S. economy. Medium-duty and heavy-duty (MDHD) vehicles account for more than a quarter of road transportation fuel use and CO_2 emissions in the United States, with a projected increase in energy consumption of 11% by 2050 [1]. MDHD vehicles account for 73% of PM2.5 (particulate matter with particles less than 2.5 micrometers in diameter) emissions globally and distribute exposure of these harmful products inequitably [2]. Plug-in electric vehicles (PEVs) are a promising alternative to petroleum-fueled transportation and have the potential to eliminate direct MDHD emissions. PEVs draw some or all of their power from the electric grid, enabling efficiency and fueling cost improvements and reducing or eliminating tailpipe emissions. However, the ability of PEVs to satisfy operational requirements for some MDHD sectors is constrained by technical challenges, including limits on driving range and long recharging times. Furthermore, the cost competitiveness of electric (e)MDHD vehicles has been limited by factors including high vehicle production costs and insufficient high-power charging infrastructure.

Still, the demand for MDHD electrification is increasing. On the MD side, Amazon, UPS, FedEx, and DHL have made commitments to purchase substantial numbers of PEVs for their package delivery fleets. On the HD side, recent analysis has suggested that long-haul freight trucks may soon be competitive with conventional trucks based on total cost of ownership (TCO) if fast-charging infrastructure is sufficiently deployed [3], [4]. To actuate ambitious EV adoption plans, such as those currently enacted at state and federal levels, requires the guidance of robust and up-to-date modeling and analysis. The timelines under which PEVs will become suitable and cost competitive in different MDHD vocations will differ across the regions of the United States. The readiness of PEVs for deployment therefore depends on varying sets of factors, for which technical, economic, and environmental assessments can define allocations and trajectories for investments in infrastructure, marketing, and products. No matter how large a role these policies play, the decentralized decision-making of fleet purchasers, vehicle and electric vehicle supply equipment (EVSE) manufacturers, energy system stakeholders, and local policymakers will continue to play key roles in defining eMDHD availability and uptake. Presently, these stakeholders have incomplete access to information and resources to inform their decision-making, which has been identified as a critical obstacle to eMDHD market development [5].

Objectives

The goals of this project are to develop and integrate two novel modeling capabilities to accomplish the goals of Funding Opportunity Announcement 2420 Area of Interest 8. The first modeling tool is a fleet-level techno-economic analysis model capable of estimating energy use and associated environmental and cost impacts for electrified and conventional vehicles of any MDHD vocation, using real-world cost and operations data, including approaches to optimizing schedules for charging and/or vehicle dispatch. The second modeling tool is a system-level, bottom-up, agent-based model (ABM) capable of generating geographically resolved estimates of market projections for MDHD vehicles and charging infrastructure. These tools will be developed together to serve dual purposes as analysis tools for researchers and decision-support tools for decision makers in the MDHD ecosystem. Illustrative applications of the integrated tool will serve to identify novel insights and opportunities to improve the sustainability, cost effectiveness, and equitability of the MDHD transportation system.

Approach

The modeling capabilities developed for this research project require drawing from distinct modeling domains. For the first tool, modeling the cost and operational suitability of eMDHD vehicles for a fleet requires a modeling framework that can be adapted to model any of the wide variety of duty cycles completed in the MDHD sector. To model vehicle and infrastructure procurement economics and their key sensitivities, the modeling framework must include bottom-up component-level cost modeling. To represent the details of any fleet's operation, the model must also include a microsimulation operating at a level of granularity fine enough to model such technologies as smart charging and ultra-fast direct current fast charging (DCFC) and to capture the significant differences in cost and operation between duty cycles and fuel sources. For the second tool, the ABM is required to characterize the potential effects of social and behavioral factors, in addition to economic, technical, and environmental factors, on eMDHD technology diffusion. Within the ABM, decision theory is applied to define the decision-making process of each type of agent.

The capabilities to be developed and integrated into these tools are highlighted in the following technical details.

Capital Costs Modeling

Although many types of PEVs have already demonstrated an economic advantage based on TCO, upfront costs for PEV are consistently higher than conventional equivalents. Additionally, fleets may need to purchase and install charging infrastructure to support PEVs, exacerbating their upfront cost disadvantage. While business purchasers exhibit more concern for TCO than typical individual vehicle purchasers, the upfront cost still plays an important role in their purchase decisions. It is therefore critical for a fleet's owners/operators to understand each of the potential capital costs of electrifying their fleet: both the cost to purchase vehicles, and the purchase and installation costs of charging equipment.

To date, many MDHD sectors have few or zero PEV options to choose from, and the vehicles that are available do not yet benefit from mass-production cost savings. Recent studies have employed bottom-up cost modeling to estimate costs of production for vehicle models that do not yet exist, and for existing models in a more mature market. In this approach, cost estimates are the sum of estimates of individual component costs and other costs (labor, overhead, etc.). LEM has provided cost data for its production models, broken down by component. These data, together with publicly available data, will be used to develop bottom-up cost estimates for eMDHD vehicles of any class and for any duty cycle. We have already used this approach and these data to model upfront costs for several types of vehicle, including delivery vans, short-haul trucks, and long-haul trucks.

The market for charging infrastructure, especially high-power DCFC, is also in its early stages. In addition to component and manufacturing costs, charging infrastructure requires costs for installation, which may include upgrading electricity infrastructure. These costs have varied widely, based on variables ranging from the capacities of transformers to the particulars of parking lot configurations [6]. This uncertainty has been yet another obstacle for electrifying fleets. A bottom-up infrastructure cost modeling tool, employing cost data provided by LEM and the Electric Power Research Institute (EPRI) and publicly available cost data, can help to reduce this uncertainty. A promising alternative is for electricity providers to handle charging infrastructure purchase and installation and to amortize the costs via the cost of charging assessed to the fleet. This business model, "Charging as a Service" (CaaS), as well as other potential charging paradigms, will be modeled and evaluated using the cost models developed for this research project.

Operating Costs and Suitability Microsimulation

For this research, we refer to microsimulation as a type of simulation in which entities—in this case, vehicles—are modeled at the individual level but have less decision autonomy than in an ABM [7]. The purpose of our microsimulation model is to estimate the suitability and cost of eMDHD vehicles for any fleet setting, i.e., any composition of vehicles performing any variety of duty cycles, operating from (and, potentially, charging at) the same home location. Inputs to the microsimulation are the objectives to be achieved by the fleet, attributes of the home site including the presence of distributed energy resources (DERs), and exogenous aspects including fuel and electricity prices. The outputs are metrics of suitability and metrics of economic performance, including operating costs.

Surveys and interviews have consistently found that fleet decision-makers consider operational suitability to be a primary factor in the evaluation of alternative-fuel vehicles [8]. While modeling studies commonly do not define what is meant by operational suitability, they tend to measure it as the capability of PEVs to follow the same duty cycles as existing internal combustion engine/vehicles (ICEV), i.e., to drive the same schedules carrying the same payloads [9]. It is likely that the optimal fleet configuration and set of duty cycles for meeting a fleet's system-level objective, such as package delivery, is different if the fleet includes PEVs than if it comprises only ICEVs. Thus, presuming a PEV fleet must follow ICEV-optimized schedules unnecessarily disadvantages PEVs. For example, adding charging stops to a duty cycle may enable sufficient PEV cost and weight reductions to counterbalance the costs of the additional stops, enabling a PEV fleet to achieve the fleet objective at an equal or lower TCO. However, the same PEV fleet denied the option to include charging stops might have insufficient range to complete the duty cycle as specified, making it appear unsuitable. The scope and resolution of our proposed microsimulation model enable optimizing within broader sets of operational suitability constraints. With the deeper understandings that a more detailed and inclusive model of vehicle operation can provide, we have modeled operational suitability as a PEV fleet's ability to complete the fleet's system-level objective, allowing for changes to fleet composition and duty cycles (and accounting for these changes in operating costs).

Operating costs encompass a variety of costs, including those for fueling/charging, maintenance, labor, equipment degradation, and more. These costs are often estimated at a coarse granularity, e.g., by estimating levelized costs and applying them over an estimated annual mileage. A finer-grained microsimulation is necessary to understand the sensitivity of operating cost to variables of interest to individual fleets, such as smart charging capabilities, utility rate structures, and the cost and availability of high-power DCFC. Our microsimulation models the driving and charging behaviors of individual vehicles in a fleet, imposing no intrinsic constraints on fleet composition, vehicle type, or operating schedule. Inputs to the microsimulation serve as technical and economic constraints and parameters. These constraints and parameters are used to define optimization problems from which optimal duty cycles and charging schedules are computed, using open-source convex optimization software. Recognizing that fleet operators can have varying objectives for their fleet designs, optimization objectives will include minimization of TCO, emissions, peak demand, and other metrics. The tool can currently optimize charging for a fixed operation schedule to minimize electricity cost under any static or dynamic utility tariff via convex optimization. It also interfaces with EPRI's open-source Distributed Energy Resources Value Estimation Tool (DER-VET) to enable evaluation of DERs at the fleet's home site to support PEV charging, such as battery storage and solar photovoltaic generation, via optimization of DER sizing and dispatch schedules.

Agent-Based Adoption Modeling

Distinct from microsimulation, ABM is an individual- level modeling technique in which "agents" are modeled to operate autonomously, driving outcomes with their decision-making. Through representation of behavioral and social aspects of decisions, as well as how market phenomena emerge from individual choices, ABM enables addressing aspects of technology adoption that conventional top-down adoption modeling approaches cannot. Many such aspects are of interest, including the effects of targeted policies and incentives, the roles played by interaction and observation, and the geographic arrangement of agents and factors for decision-making.

Adoption models often focus either on demand or supply, but the market will be driven by the interaction between supply and demand, both of which can serve as a constraining factor for different segments of a market. For example, there is potential for a “chicken-or-egg” predicament, where vehicle uptake remains low because of a lack of vehicle and charging infrastructure availability, and, conversely, infrastructure and vehicle supply remain low in response to a lack of vehicle demand and utilization. Thus, eMDHD system growth is likely to involve a complex coevolution of supply and demand driven by feedback loops between producers, purchasers, and energy and infrastructure suppliers.

To address these dynamics, agents in our model include fleet operators, manufacturers of vehicles, and utility and infrastructure managers. Policy decisions are treated as inputs to the adoption model. Each of these agent varieties makes decisions in pursuit of its individual objectives, based on the subset of information available and according to individual preferences and risk characteristics. The decisions of agents exert mutual influence in a variety of ways. For example, an electric utility installing a set of fast charging stations improves the suitability and TCO of PEV for fleets in the surrounding area, increasing their likelihood to adopt PEVs. The adoption of PEVs, in turn, increases the utilization and payback potential of the charging stations. Furthermore, fleets driving similar duty cycles elsewhere might observe the uptake, increasing their familiarity and confidence in PEVs and potentially encouraging them to adopt PEVs. These and myriad other means of feedback and diffusion can be investigated via ABM.

The mechanism of decision-making is essential in defining an ABM. Ours is defined using a combination of theory and empirical study. In contrast to the purchasing choices of individual consumers, which typically involve hard-to-quantify factors such as perceived norms, symbolism, and emotions, business decisions such as those for fleets are heavily influenced by well-understood economic factors like TCO. In some adoption models, business decision-makers are approximated to adhere strictly to utility theory, wherein they invariably make the purchase with the highest “utility” (e.g., always choose the option with the smallest TCO). However, this can lead to unrealistic dynamics if “utility” is defined too narrowly. Researchers have previously employed the theory of planned behavior to model decision-making in fleet settings [10]. This theory enables quantitative modeling of factors such as attitude, familiarity, and perceived operational ease associated with a technology, which have been shown to play a role in the decisions of fleets and other businesses. In our model, the theory of decision-making followed by agents will incorporate aspects of both utility theory and theory of planned behavior.

Empirical studies of the decision process followed in fleet settings have been conducted for decades, primarily through such means as surveys, interviews, and focus groups. For example, researchers as far back as 2001 found that “bureaucratic” fleets (typical to the public sector) are unlikely to respond to incentive-based policies but are responsive to mandates, whereas “hierarchic” fleets (typical to larger companies in the private sector) exhibit the opposite behavior [11]. Decision-making preferences are also found to differ significantly for strategic, non- routine decisions (such as electrification) and for urgent decisions such as might be spurred by policy mandates.

In summary, an agent modeling framework is defined by 1) the types of agents being modeled and 2) the decision theory followed by agents. To put a framework to use, it must be populated using real-world or synthetic data. This entails quantifying and distributing agent attributes, including decision-making preferences and fleet characteristics. Fleet characteristics, including fleet size and vocation, will be initialized from publicly available data and data provided by partners. Decision-making characteristics, such as the relative weights of key metrics including TCO and upfront cost, will be initialized based on results of studies in the literature correlating decision preference with fleet characteristics.

Results

In Budget Period 1, the capital costs modeling and operating costs microsimulation tools were developed, validated, and demonstrated.

An example analysis case, where the tools were applied to estimate costs for a collection of commercial EV fleets, illustrates the capacity of the microsimulation tool to co-optimize charging schedules with energy storage and generation to reduce costs. In this instance, it is assumed that a CaaS operator serves as an intermediary to own and operate charging equipment, in addition to a commercially-sized microgrid, equipped with a solar photovoltaic (PV) array to generate power and a storage battery to enable adjusting when power is drawn from the grid. The CaaS provider also manages the accrual and sale of low-carbon fuel standard (LCFS) credits for EV charging. Because LCFS credits scale with the carbon intensity of the energy source, these two functions are interrelated, including that increased usage of the PV array increases the revenue possible from LCFS. Although fleets are not prevented from generating and selling LCFS credits independently, few electric fleets have done so to date [12]. Recognizing the complexity of applying for, obtaining, and selling LCFS credits, we assume all steps of the LCFS process to be handled by the CaaS credit accounting provider. We also assume the microgrid can be used to serve multiple separate fleets.

We estimate the costs associated with charging multiple geographically proximal, operationally diverse fleets, all of which are subject to a single electricity pricing model and are served by a single CaaS provider. In our CaaS scenario, all EVSE and microgrid resources are jointly owned by the CaaS provider and are controlled to minimize net operating expenses, including revenues from LCFS. In our baseline scenario, each fleet controls charging to minimize cost, but they do not access microgrid resources or LCFS revenues. We estimate costs for varying numbers of fleets, ranging from 1 to 25, each of which comprises 20 Class 3 electric vans. Each fleet functions for either package delivery or passenger transport, the driving and charging behaviors of which are modeled after those of real electric fleets. Key assumptions are summarized in Table III.4.1.

Table III.4.1 Key Assumptions for the Example Case

Category	Parameter	Value	Units
Economics	Annual discount rate	7	Percent
Economics	System lifespan	10	Years
Economics	LCFS credit price	150	$/metric ton
Economics	Electricity pricing	Commercial EV Rate (Southern California Edison)	
Microgrid	Battery power capacity	600	kW
Microgrid	Battery energy capacity	2.4	MW
Microgrid	Solar power capacity (nominal)	1	MW
Microgrid	System cost	1.97	Million $
Operation	Mean/maximum daily distance (passenger fleets)	91.4 / 337.9	km
Operation	Mean/maximum daily distance (cargo fleets)	80.4 / 271.0	km
Vehicles	Vehicle type	Electric Class 3 van	
Vehicles	Energy consumption rate	327	Wh/km
Vehicles	Battery capacity	73.6	kWh
Vehicles	Electric range	225	km
Vehicles	Number of vehicles per fleet	20	

Figure III.4.1 illustrates the coordinated dispatch of EVSE and DERs in the CaaS scenario, in contrast with baseline charging operation, when CaaS serves 3, 10, and 25 fleets. Whereas baseline charging management strictly avoids high electricity prices in the evening, CaaS charging management optimizes across several objectives: actualizing and maximizing LCFS revenues based on the time-varying value of LCFS credits; reducing the total energy purchased from the grid by means of DER system resource dispatching; avoiding the purchase of expensive evening power; and meeting the various constraints of the DER system and the energy requirements of the fleets. As it serves more fleets, the DER system's capacity is more fully utilized, while its relative savings potential decreases. At the extreme, when serving 25 fleets, the peak charging demand is quadruple the PV generation peak, limiting the DER system's ability to meaningfully reduce grid power demand.

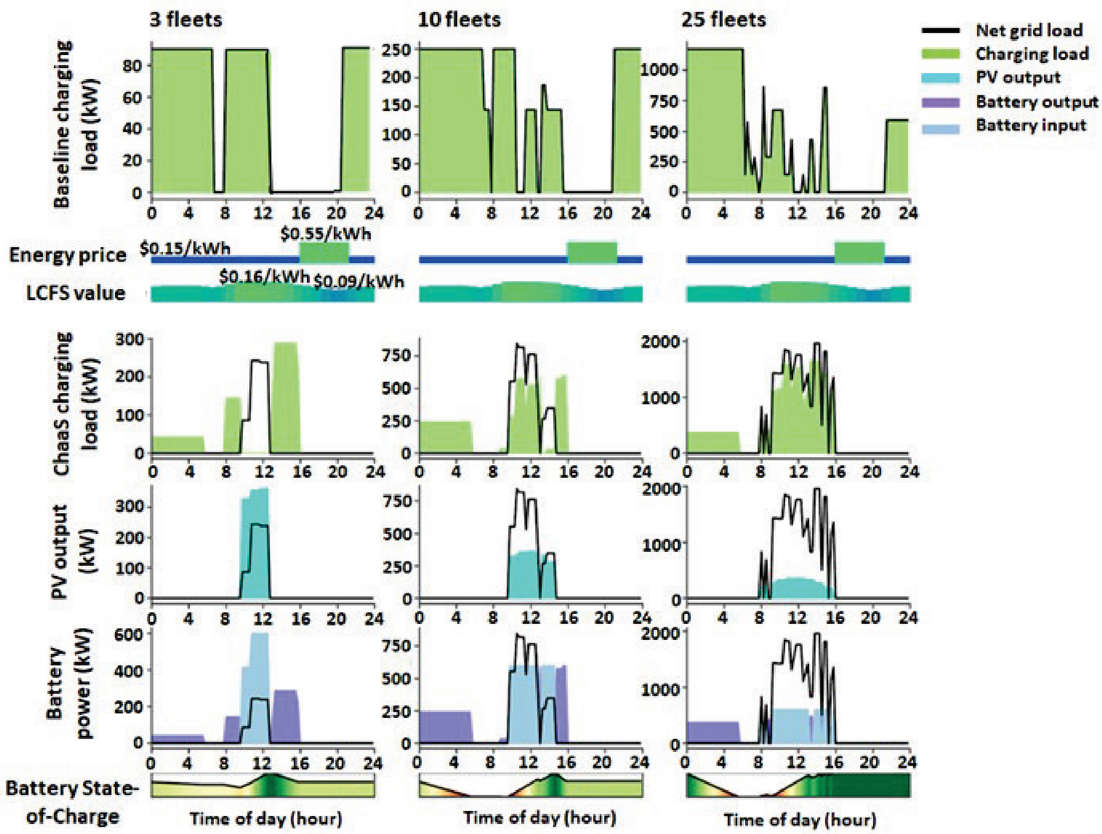

Figure III.4.1 Baseline charging comparison with CaaS, PV output, battery power and the battery state-of-charge. Source: Colorado State University

Figure III.4.2 compares the levelized cost of charging (LCOC) across scenarios for varying numbers of fleets. Serving more fleets, by increasing DER utilization, reduces the fraction of LCOC devoted to repaying upfront costs for the DER system. However, the DER system never realizes a net benefit compared to the non-DER alternative, suggesting that the DER system we reference is too expensive to pay back solely from avoided grid demand and the differential revenues from zero-carbon LCFS credits, even at maximum utilization. In contrast, LCFS revenues, with or without DERs and irrespective of the number of fleets served, actualize substantial LCOC reductions.

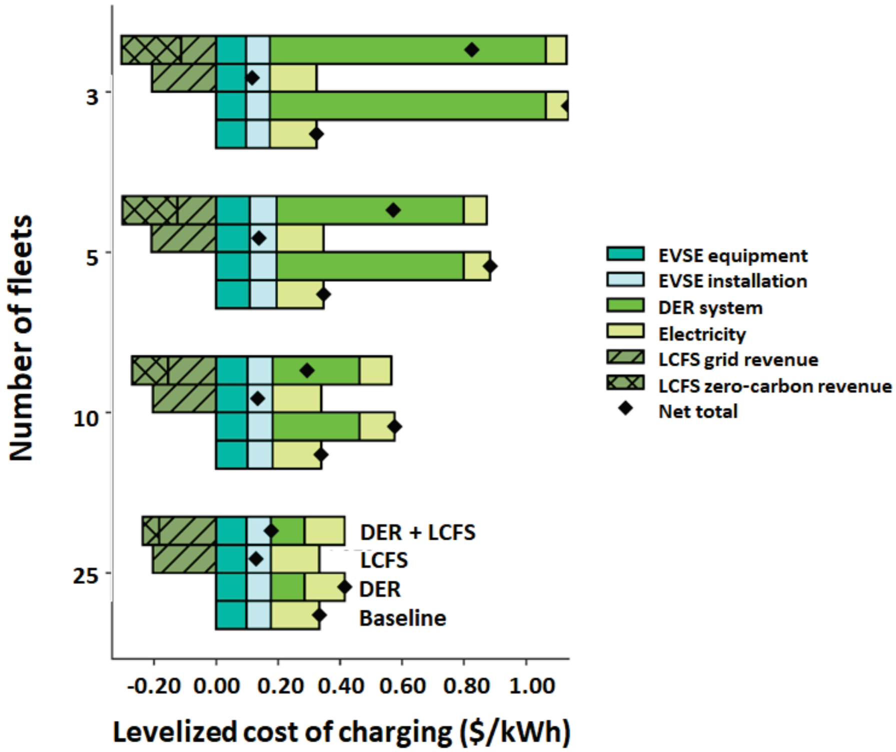

Figure III.4.2 Levelized cost of charging for various number of fleets and scenarios. Source: Colorado State University

Conclusions

This example illustrates how scale and diversity improve the savings and revenues realizable via DER dispatch. While the DER system we modeled may not be economically justifiable in the scenario we present, it may become so in a place with higher grid electricity prices, lower DER system costs, or a more carbon-intensive grid. Although we find that LCFS revenues can drastically reduce LCOC at any scale, a large electric fleet—or an aggregation of small ones via CaaS—may be necessary to justify actualizing LCFS revenues depending on participation costs (application, approval, sales), which we did not model. Both value streams may thus be infeasible for small fleets to access without CaaS.

Key Publications

1. Trinko, David, Noah Horesh, Emily Porter, Jamie Dunckley, Erika Miller, and Thomas Bradley. 2023. “Transportation and Electricity Systems Integration via Electric Vehicle Charging-as-a-Service: A Review of Techno-Economic and Societal Benefits.” *Renewable and Sustainable Energy Reviews* 175: 113180. doi:10.1016/j.rser.2023.113180.

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Acknowledgements

The authors would like to acknowledge the research and program management team including Erika Miller, David Trinko, Fletcher Ouren, Marcus Alexander, Brian Johnston, Jeff Anders, and Michele Foster.

III.5 Scalable Truck Charging Demand Simulation for Cost-Optimized Infrastructure Planning (ElectroTempo, Inc.)

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Start Date: October 1, 2021 End Date: December 31, 2024
Project Funding (FY22): $161,578 DOE share: $143,988 Non-DOE share: $17,157
Total Project Funding: $360,000 DOE share: $324,000 Non-DOE share: $36,000

Project Introduction

Widespread truck electrification requires strategically planned public and private charging infrastructure. Truck electrification offers high potential for climate, environmental, and equity benefits. The Environmental Protection Agency (EPA) reported in 2020 that medium- and heavy-duty trucks accounted for 26.3 percent of U.S. carbon dioxide emissions from fossil fuel combustion. [1] The EPA also reported that about 72 million people live within 200 meters of a freight route, and that people of color and those with lower incomes are more likely to live near those routes. [2] Truck electrification also poses the biggest threat to the grid, due to its high, concentrated, and inflexible charging demand. According to Oncor, a Texas utility, a few customers electrifying only a few vehicles each simultaneously could overload substations, yet there are 21,600 fleets with two or more vehicles that operate in Oncor's service area. [3]

No solutions currently exist to forecast truck charging demand for grid planning. Traditional commercial travel models do not have energy components. Integrated urban models such as Polaris and the Behavior, Energy, Autonomy, and Mobility models are not for state- or national-level analysis, which is required for freight corridor planning. National level models such as Transportation Energy and Mobility Pathway Options and the Freight Analysis Framework are spatially resolved at the county level, which is not detailed enough for grid planning. Fine-grained truck charging demand forecast is challenging because truck data is scarce. Scaling urban models to regional and state levels is also cost prohibitive for data acquisition and technical development.

This project overcomes the challenges of data scarcity and model scalability through a modular platform of generative models and large-scale co-simulation of transportation and grid systems.

Objectives

The objectives of the project are to (1) develop a truck charging demand model for large urban areas and along highway corridors and (2) demonstrate cost-optimization strategies for placing and sizing charging infrastructure that balance grid upgrade costs and greenhouse gas and air pollutant costs.

In Budget Period 1 (October 2021 - December 2022), the objective was to develop a megaregion electric truck charging simulation model with distinct urban and long-haul truck considerations, temporally resolved to the hour and spatially resolved up to the street block.

Approach

This project's modeling platform combines modular architecture, data science, and simulation to address the current lack of truck charging demand forecasts.

The parallel modules of simulation and machine learning methods for each component of a transportation-energy modeling system are especially applicable to truck charging demand modeling due to the lack of mature models and real-world data at various stages and resolution levels in the modeling process. The project explores diverse truck data sources and develops algorithms to fuse these data sources and generate realistic synthetic data for system simulation. In the next budget period, we will automate and streamline the transportation and grid models, independently and jointly, such that the time required to conduct a coupled infrastructure study is reduced to hours. We will demonstrate an approach to reconcile the differences of spatial resolution and scale between the simulations of the two infrastructure systems.

Results

Urban (Short-Haul) Truck Simulation

The team developed a base urban truck simulation model. We used the Houston regional travel demand model and a Bayesian network model trained on the Houston commercial vehicle survey [4] to simulate trip attributes including origin county, arrival hour, vehicle type, and trip energy consumption. A Bayesian network model is a machine learning method that measures the conditional dependence structure of a set of random variables based on the Bayes theorem [15]. The simulated trips were used to assign charging demand at destinations across the Houston region.

The initial simulation results indicate that the total charging demand of all short-haul trucks in the 8-county Houston area is 24.0 GWh. According to the Highway Performance Monitory System data released by the Texas Department of Transportation (TxDOT) [5] and the TxDOT Houston District Truck Mobility Study [8], the short-haul truck VMT is approximately 9.8 million miles. Assuming an energy consumption rate of 2.74 kWh/mile based on peer-reviewed literature [6], the top-down estimate of total energy consumption of short-haul trucks in the Houston region is approximately 26.8 GWh if they were all electric. The simulation results are within 10% of the top-down estimate.

Next, we improved the spatial resolution of truck charging behavior and energy consumption under our model by inferring likely charging locations and fleet mix. We use multiple data sources:

- Land-use parcel data from the metropolitan planning organization
- County business property databases
- Fleet inventory databases such as FleetSeek™
- Point of interest.

Identify Locations with High Probability of Truck Charging

For every land parcel in the Houston region, we estimated its probability of being a truck depot. Parcels with high depot probability are eligible to be assigned overnight charging demand from simulated battery electric trucks. The team used a neural network to model depot probability. The team manually labeled about 1,200 land parcels as “True” or “False” for truck depots. The dataset was split in two: one dataset for training and another for testing at an 80/20 ratio. The accuracy of the neural network model was 92.6% for the training set and 91.1% for the testing set. The team also supplemented the neural network model with a traditional logistic model to overcome the potential overfitting issue that most machine learning models tend to have.

We spatially joined the depot predictions to the transportation nodes in the base charging demand simulation. This increased the spatial fidelity of truck charging demand, due to a higher concentration of charging demand in major logistic centers. Figure III.5.1 depicts the concentration of depots across Houston.

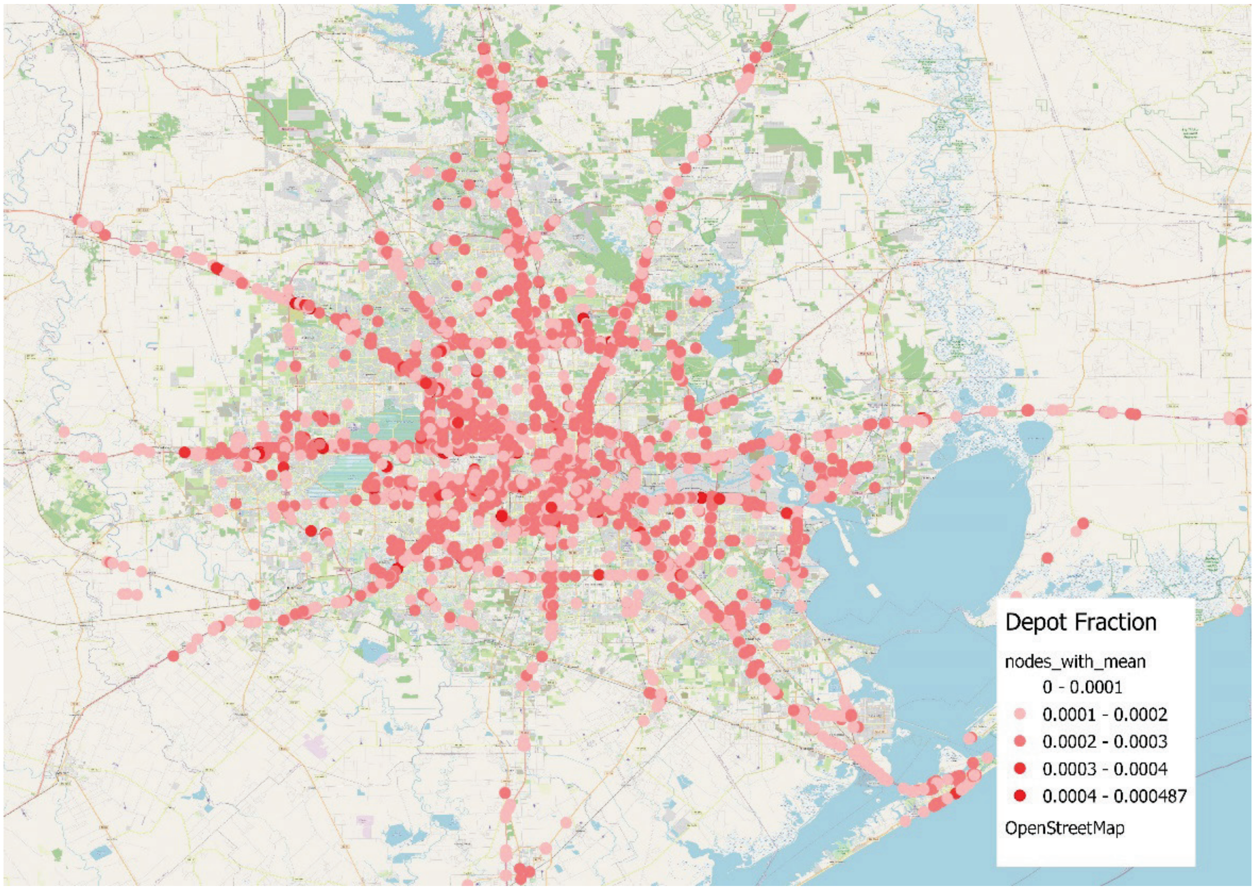

Figure III.5.1 Predicted truck depot concentration for Houston. Source: ElectroTempo, Inc.

Construct Database of Energy Consumption by Truck Type

The team collected truck energy consumption information for 86 different truck models for which public information is available. This inventory is further mapped to the vocational truck types in the National Renewable Energy Laboratory's (NREL) FleetDNA dataset. [7] The energy consumption rates derived from the advertised maximum range are lowered based on the expectation that the energy consumption rates in real-world operations are typically higher than in the labeled fuel economy.

The team used both a specialized fleet dataset and Google Maps to associate truck weight classes with operational types and, ultimately, to NREL FleetDNA truck types for further processing. In the process, the team also identified the fleets as small, medium, and large as an additional attribute.

We validated our urban truck traffic generation process using the Highway Performance Monitoring System data released by the TxDOT. The average, pre-pandemic truck vehicle miles travelled (VMT) within the region was 11,129,005 (years 2018 and 2019). According to the TxDOT Houston District Truck Mobility Study [8], 88% of the truck traffic in the Houston area is within-region (i.e., short-haul). Therefore, the short-haul truck VMT can be calculated to be 9,793,524 miles. The ElectroTempo charging demand simulation estimates that there are 791,178 short-haul truck trips in the region. According to the Houston area commercial vehicle survey [4], the average trip length of truck trips is 13.5 miles. Therefore, the total VMT estimated from the charging demand simulation is 10,680,903 miles. The difference between the estimated VMT and the real-world VMT is 9.1%.

Transfer Charging Demand Simulation Framework to Dallas Region

We demonstrated the portability of our urban truck charging demand simulation by implementing it for the Dallas-Fort Worth metropolitan area as depicted in Figure III.5.2. As with Houston, we modeled depot probability in the Dallas region. We trained a random forest model in addition to the logistic and neural network models we trained for Houston. Our model performed well; the ensemble precision and recall levels are both above 97%. The process identified 18,193 depots from 13,523 companies.

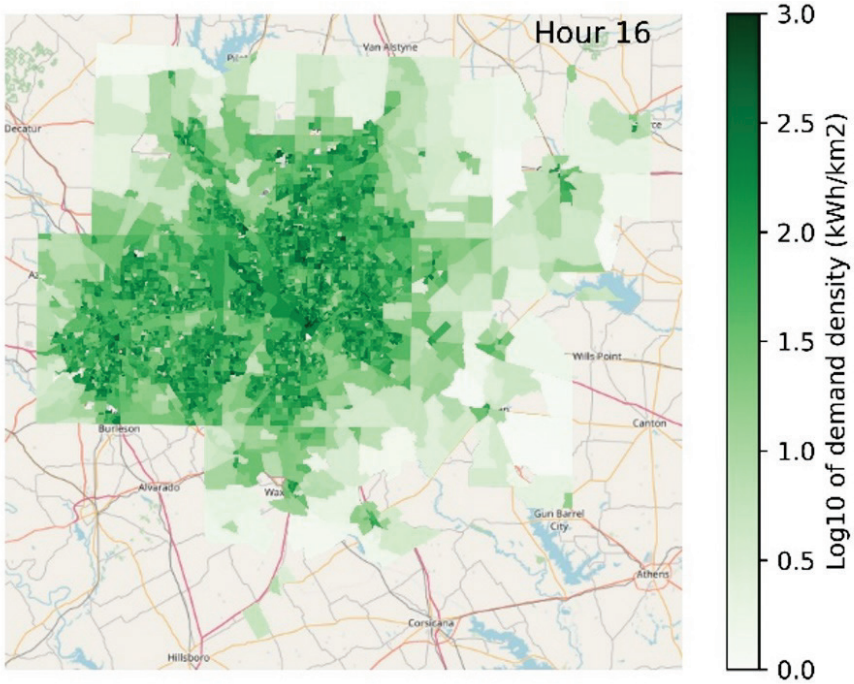

Figure III.5.2 Hourly charging demand simulation at 4pm for Dallas, as an illustration. Source: ElectroTempo, Inc.

Regional (Long-Haul) Truck Simulation

To estimate charging demand on the I-45 corridor between Dallas and Houston, the team devised a scalable method to translate origin-destination commodity flows into probable truck routes on the U.S. highway system. We used the Freight Analysis Framework [9] as the source of commodity flows and the Open-Source Routing Machine [10] to identify which highways trucks traverse between origin-destination flows. We identified all tours that either shuttle between Houston and Dallas, originate in Houston and end in regions other than Dallas, originate from Dallas and end in regions other than Houston, tours that originate from elsewhere and end in Houston or Dallas, and tours that begin and end elsewhere but traverse the study area of I45.

We assigned depot charging probability logic to truck trips on I-45 based on their origins and destinations:

- Tours that shuttle between Houston and Dallas: Trucks will start out on (almost) full battery and will only need to charge enough to finish the 250-mile stretch.
- Tours that originate from Houston or Dallas and end in other regions: Trucks will start full and will need a full charge when they get to a charging location if the state-of-charge falls below a threshold of 60% battery.
- Tours that originate from outside the study area and end in either Houston or Dallas: Trucks will arrive at charging locations with batteries (almost) depleted but will only need to charge enough to get to the destination.

- Tours that originate and end outside the study area and traverse the I-45 corridor: Trucks will need a full charge.
- Tours that originate and end outside the study area and intersect the I-45 corridor at the charging depot: Trucks will need a full charge.

We used the 2022 North Central Texas Council of Governments (NCTCOG) I-45 Corridor Zero Emission Vehicle (ZEV) Plan [11] to identify potential charging depot locations along the corridor. In NCTCOG's ZEV plan, there are three candidate sites for charging infrastructure to support electrified freight movement (Exits 118, 178, and 229). We implemented the charging demand simulation at each of the three sites along the corridor. We considered each site independently, assuming only one charging location on the corridor at a time.

Using 2018 annual tonnage by the origin-destination pair in the Freight Analysis Framework, we estimate long-haul truck traffic by trip type (traversing or intersecting I-45). We assumed a typical payload of 15 tons and that trucks drive 300 days a year. We estimate that in 2018 the daily truck traffic traversing I-45 was 9,637 trucks. According to the National Freight Commodity Corridors tool (FHWA, 2021) [12], there were approximately 10,800 daily trucks on the I-45 corridor between Houston and Dallas in 2018. This estimate is about 11% different from our estimate. We found that charging demand would be highest if a single depot was installed at the site proposed at Exit 178, which is closest to the midpoint between Dallas and Houston.

We also used the Institute of Transportation Engineers Trip Generation Manual 11th Edition [13] to estimate truck arrival rate per hour at a typical truck stop. We applied the arrival distribution to the total daily demand to estimate hourly charging demand as depicted in Figure III.5.3.

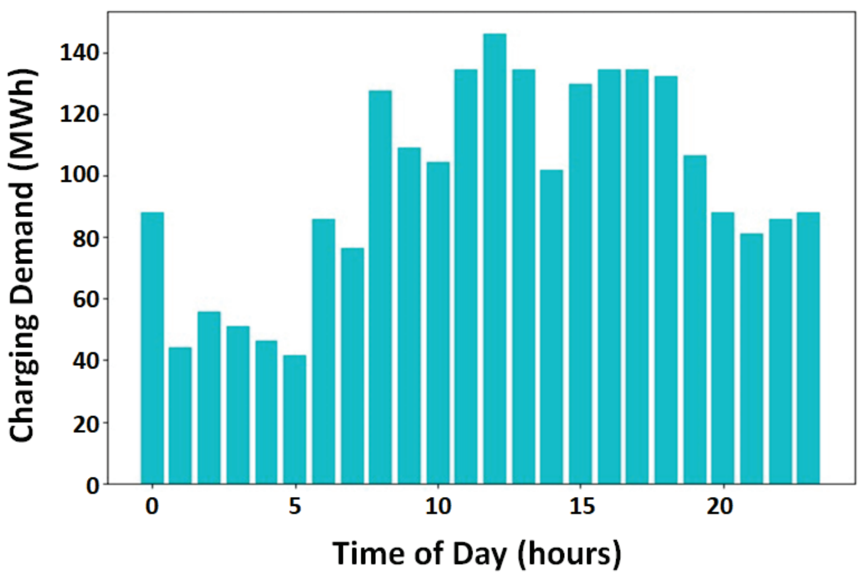

Figure III.5.3 Estimated hourly long-haul heavy-duty truck charging demand at Exit 178 of the Houston-Dallas I-45/US 79 corridor. Source: ElectroTempo, Inc.

We compared our heavy-duty truck load profile with a recent independent analysis. The California Energy Commission in 2021 estimated a statewide load curve associated with battery electric medium- and heavy-duty trucks. [14] The California statewide load profile associated with tractor-trailer trucks (heavy-duty trucks) closely resembles ours, i.e., charging demand is lowest in the early morning, begins rising around 8am, and is highest during the hours between 8am and 5pm as can be seen in Figure III.5.3.

Conclusions

The team developed a megaregion electric truck charging simulation model with distinct urban and long-haul truck considerations, temporally resolved to the hour and spatially resolved up to the street block. We validated both our estimated truck traffic patterns and load profiles with top-down data sources or other independent analyses. We have tested the entire simulation pipeline for the study area on an Amazon Web Services Elastic Compute Cloud instance. The combined urban and long-haul truck charging demand simulation completes with runtime under 10 hours for a region. We demonstrated that our modular modeling framework can be scaled to new regions.

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IV Energy and Emissions Modeling

IV.1 Assessing Energy and Cost Impact of Advanced Vehicle Technologies (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (FY22): $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. The work described relies on Autonomie [1], a simulation tool developed by Argonne National Laboratory (ANL), to quantify the energy consumption and cost of technologies funded by the Vehicle Technologies Office (VTO). This work also employs Benefits Analysis (BEAN), a technoeconomic analysis tool developed by ANL, to quantify the technology benefits and emissions associated with advanced vehicle technologies [2]. The project integrates VTO-sourced data on component-level technology performance and cost to generate vehicle-level metadata based on U.S. standard driving cycles. The Autonomie vehicle models and results are used to support several activities within VTO (e.g., life cycle analysis, economic impact, market penetration, and individual component technology targets), as well as outside of VTO.

Objectives

The main goals of this project were to:

- Quantify the benefits 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, cost, and detailed component information, including power, energy, cost, efficiency, and operating conditions on the U.S. standard driving cycles.

Approach

To achieve the objectives outlined above, ANL identified and completed the tasks shown in Table IV.1.1.

Table IV.1.1 ANL Project Tasks

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

The scope of Task 1 extended from small passenger cars in light-duty segments to large, long-haul trucks in heavy-duty segments. We identified several vehicles as representative of the extensive variety of vehicles in the light-, medium-, and heavy-duty segments, examining the differences in vehicle requirements and use cases for 10 types of light-duty vehicles and more than 20 types of medium- and heavy-duty trucks. The assumptions used to define these vehicles were based on inputs provided by VTO and transportation decarbonization analysis conducted by the Hydrogen and Fuel Cell Technologies Office [3]. This work used updated powertrain and sizing assumptions based on these inputs.

The main simulation tools used for this work were Autonomie and BEAN; the latter provides a convenient interface for users to examine the sensitivity of a vehicle's total cost of ownership (TCO) to 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 the U.S. Department of Energy (DOE) and to industry, quantifying the monetary benefits to the consumer of incremental improvements to these components. We examined cargo load, accessories, designed range of battery electric vehicles (BEVs), and other characteristics to help identify the technologies that yield the greatest return on investment for both manufacturers and consumers.

Analysis Results

Results from this year's (fiscal year [FY] 2022) analysis activities are provided by task below.

Task 1. Quantify vehicle energy consumption and cost estimation

The primary output of this task is a report that details the assumptions, vehicle sizing, and simulation results for both light-duty and medium- to heavy-duty vehicles. The databases accompanying the report provide all vehicle-level assumptions, fuel economy observed on regulatory cycles, and estimated manufacturing cost and operational cost for each vehicle. The FY 2022 report and the databases are accessible from the ANL Vehicle and Mobility Systems Department website [4].

This dataset forms the basis of life cycle analyses and other DOE-funded market penetration predictions. The Annual Technology Baseline project conducted by the National Renewable Energy Laboratory [5] also relies on the vehicle simulation results from this work.

The report presents a brief overview of the results available in the database. We modeled vehicles and technologies for future timeframes, examining two potential scenarios for technology progress: (1) a "business-as-usual" scenario (low) and (2) a more aggressive level of technology progress (high). The simulation results provide insights into how the different vehicle component requirements are likely to change in future years with technology advances. In addition to the component requirements, the database provides information on projected vehicle-level cost, weight, energy consumption, and cost of driving and ownership for various powertrains, as well as different emission metrics. This additional information improves our understanding of when advanced powertrains might achieve functional and economic parity with other competing choices.

Figure IV.1.1 shows the cost parity of BEVs for passenger cars (small sport utility vehicle [SUV] class). The BEV cost is compared with that of a conventional spark-ignition (SI) turbocharged vehicle of the corresponding analysis year. For small SUVs, considering current technology progress trends (low technology scenario), BEVs will become cost-competitive with conventional powertrains between the 2025 (BEV 200 miles) and 2040 (BEV 500 miles) model years. Under the high technology scenario, BEVs become cost-competitive an average of five years earlier, significantly accelerating their market adoption.

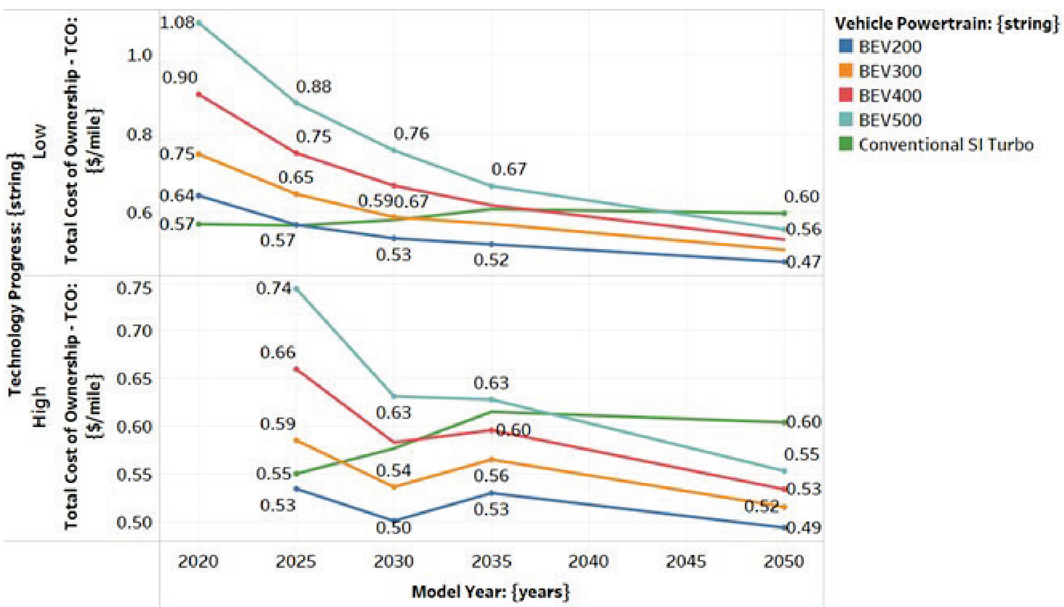

Figure IV.1.1 TCO comparison across powertrains for small SUVs. Source: ANL

Figure IV.1.2 shows the weight, cost, energy consumption, and TCO for conventional, fuel cell hybrid electric vehicles (FCHEV) and BEVs as a function of the corresponding values of the conventional diesel truck. For Class 4 delivery trucks, considering current technology progress trends (low technology scenario), BEVs will achieve TCO parity with conventional vehicles as soon as the 2028 model year. Achieving high technology progress would accelerate the timeframe by two to three years. FCHEVs are expected to achieve TCO parity by 2030, ten years earlier than in the low technology scenario.

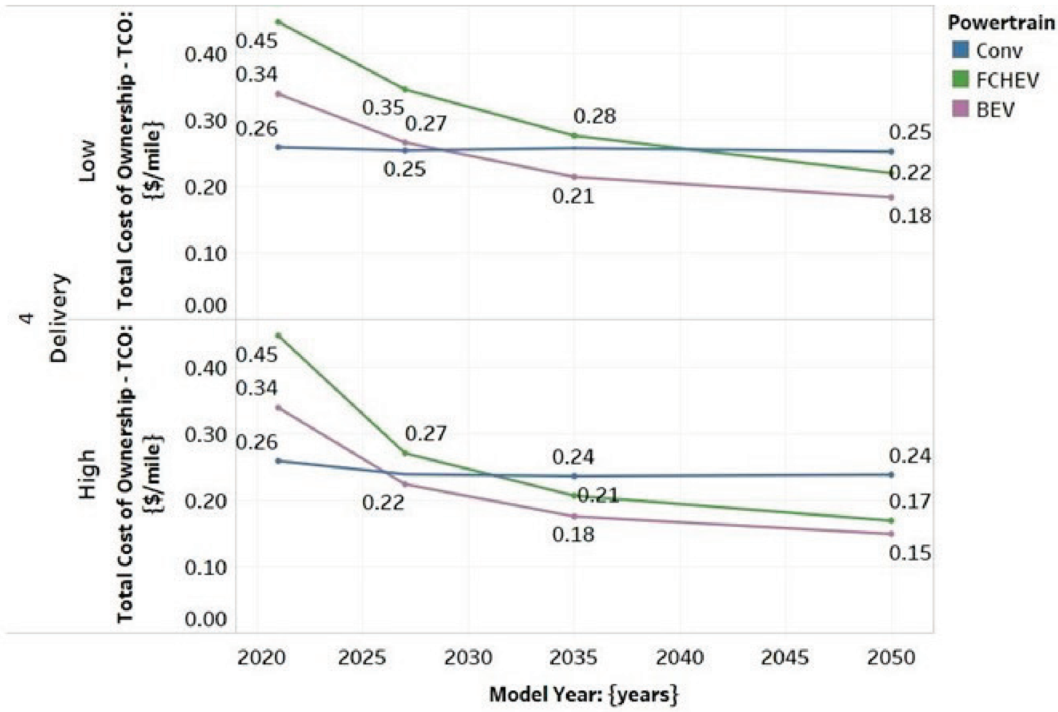

Figure IV.1.2 Evolution of vehicle cost, weight, and energy consumption for long-haul trucks that use advanced powertrains (all percentages are computed based on the conventional truck parameters for that year). Source: ANL

This analysis projects a gradual reduction in 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 achieved.

Task 2. Analyze Impact of Vehicle Operational and Design Parameters on Energy Consumption and Cost

Task 2 involved a sensitivity analysis of the following operational and design parameters for trucks: cargo weight, accessory loads, and quantification of the economic feasibility of varying the desired electric range for BEVs.

For the first part of this task, we measured the impact of cargo load and accessory loads for medium- and heavy-duty trucks. While both these factors have a linear relation to the energy consumption of vehicles, the impact varies for each truck type and drive cycle as shown in Figure IV.1.3. The blue and orange lines show the fuel consumption estimate of a Class 8 long-haul truck under zero and maximum cargo conditions. The gray line shows the percentage change between the two cases. As the vehicle becomes more efficient in future years, the additional fuel consumed due to the increased cargo mass has a more prominent share in overall energy consumption. As trucks become lighter, the cargo mass can be increased to keep the truck weight close to the maximum limit prescribed for the class. This, too, contributes to the higher impact of cargo load in future years.

Similar analysis was conducted with two levels of accessory loads. For this case, a minimum load of 300 W is used, assuming the power needed to meet the vehicle controller needs. The maximum load is set to 5 kW to account for use of air conditioning. Each vehicle may have additional loads (e.g., fans, pumps), but we adopted two arbitrary loads to complete this parametric sweep in order to determine the impact of accessory loads.

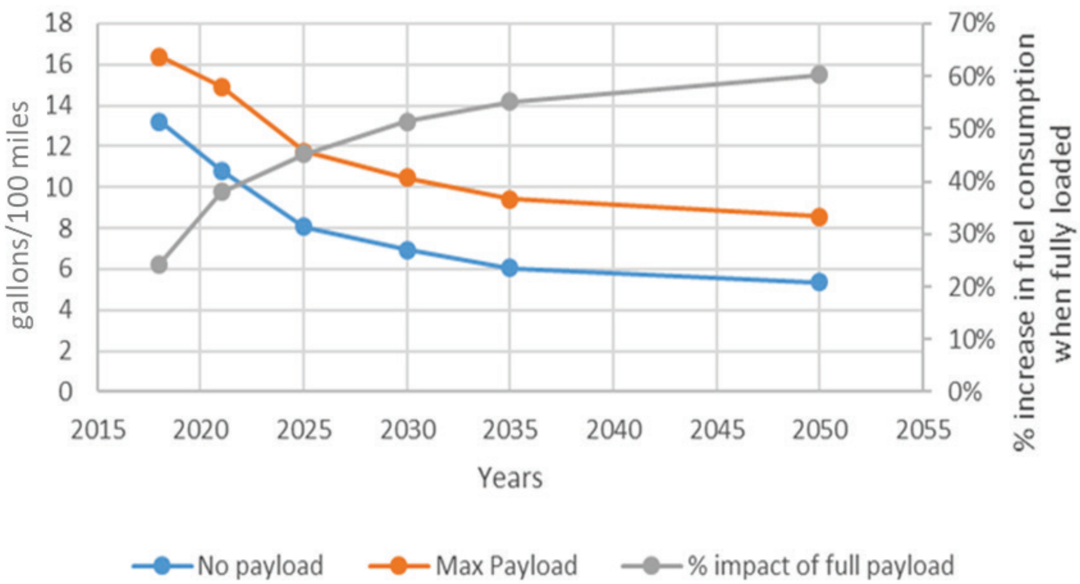

Figure IV.1.3 Impact of different cargo loads on fuel consumption of trucks. Source: ANL

These loads are applied as steady loads across the whole drive cycle. Regulatory cycles from EPA are used in this analysis [6]. The overall impact of the additional energy consumption also depends on the drive cycle characteristics; a mild cycle, such as Air Resources Board Transient, will see a higher percentage impact on overall energy consumption when a high accessory load is applied. This result applies across all vehicle classes considered. Figure IV.1.4 shows the impact of accessory loads on a Class 4 truck and Class 8 truck.

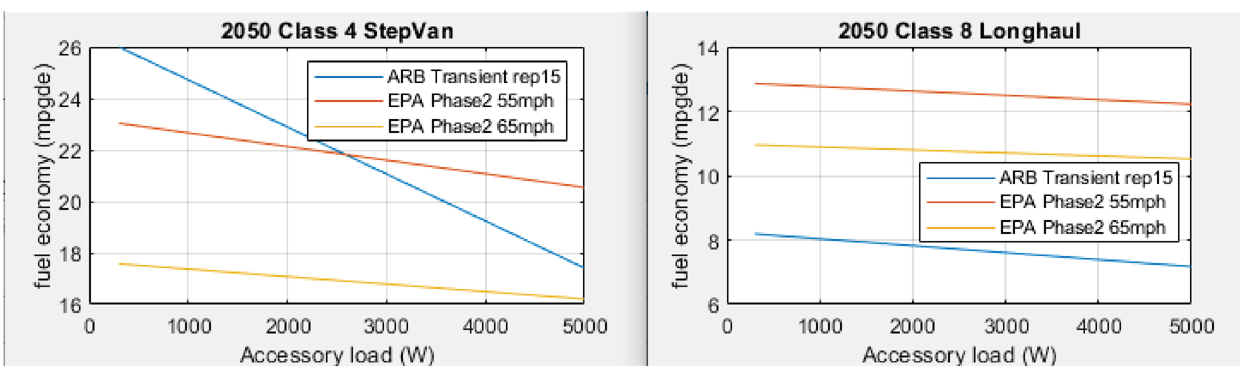

Figure IV.1.4 Impact of different accessory loads on fuel economy of Class 4 and Class 8 trucks. Source: ANL

The second part of this task included analyzing the economic viability of the designed range of electric trucks. In different target-setting activities for trucks (e.g., 21st Century Truck Partnership), the battery pack of BEVs is sized for the worst-case driving scenarios, which results in costlier battery packs and vehicles. The goal of this subtask was to evaluate the economic viability of different-range BEVs considering range requirements based on real-world data. Using the data from CALSTART and FleetDNA [7], we determined the range requirements for this analysis.

Figure IV.1.5 shows the economic viability of heavy-duty trucks when driven for the 80th–99th percentile range (from FleetDNA data). In this study, we assumed that if the daily driving exceeds the designed range, the driver will provide fast charging during the day. Long haul drivers are mostly paid for the distance they drive, so drivers needs to be compensated for the downtime associated with charging a truck. This is considered in this work by applying a dwell time penalty of $75/hour for charging.

Figure IV.1.5. shows that the cost of driving (in $/mile) is significantly influenced by the designed range, as well as the miles of daily driving. In the near term, a designed range of 250 miles would be a good tradeoff between high initial battery cost and the dwell time penalty. This choice differs in future years as the upfront battery costs (and vehicle costs) significantly decrease in response to technology improvement.

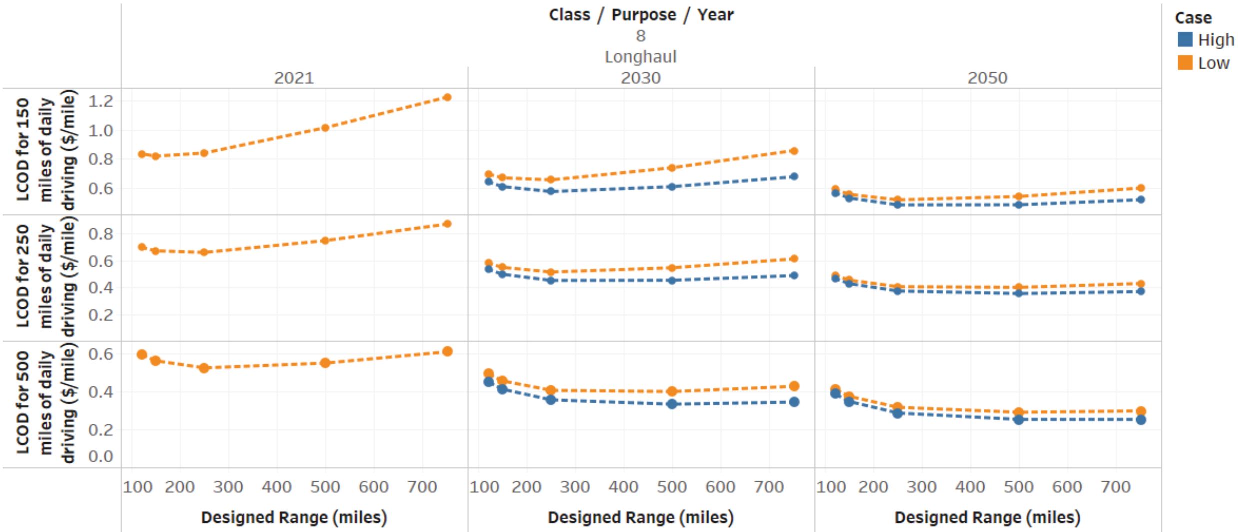

Figure IV.1.5 Impact in cost of driving for different designed BEV ranges across different miles of daily driving, including a dwell time penalty of $75/hour. Source: ANL

Conclusions

The ANL team completed the tasks planned for FY 2022 and prepared a detailed report and multiple conference and journal publications documenting the work. The final report covers the energy consumption, performance, and cost of light-, medium-, and heavy-duty vehicles [4]. The simulation and data analysis support provided for cradle-to-grave analysis activities has helped various technical teams identify appropriate technology development goals.

Key Publications

1. Islam, E., R. Vijayagopal, et al. 2022. A Comprehensive Simulation Study to Evaluate Future Vehicle Energy and Cost Reduction Potential. Report to DOE, Contract ANL/TAPS-22/1. October. https://vms.taps.anl.gov/research-highlights/u-s-doe-vto-hfto-r-d-benefits/.

2. Islam, E., R. Vijayagopal, N. Kim, A. Moawad, and A. Rousseau. 2022. "Detailed Assessment of Future Electrified Vehicles through 2050 Based on U.S. DOE Research and Innovation." Paper presented at the 35th International Electric Vehicle Symposium and Exhibition, Oslo, NO. June 11–15.

3. Islam, E., R. Vijayagopal, N. Kim, A. Moawad, and A. Rousseau. 2022. "Detailed Assessment of Fuel Cell Vehicles through 2050 Based on U.S. DOE Research and Innovation." Paper presented at the 35th International Electric Vehicle Symposium and Exhibition, Oslo, NO. June 11–15.

4. Islam, E., A. Moawad, N. Kim, and A. Rousseau. 2020. "Vehicle Electrification Impacts on Energy Consumption for Different Connected-Autonomous Vehicle Scenario Runs." *World Electric Vehicle Journal* 11, no. 1 (March). doi: 10.3390/wevj11010009.

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V Application and Accounting

V.1 Distributions of Real-World Vehicle Travel (Argonne National Laboratory)

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Start Date: October 1, 2019 End Date: March 31, 2023
Project Funding (Initial): $150,000 DOE share: $150,000 Non-DOE share: $0
Project Funding (FY22): $250,000 DOE share: $250,000 Non-DOE share: $0
Total Project Funding: $400,000 DOE share: $400,000 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 a vehicle ages. These schedules are used to calculate levelized cost of driving (LCOD) and cradle-to-grave environmental life cycle 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 consumption.

Furthermore, driving behavior is not homogenous, and using a single mileage schedule for all calculations related to life cycle emissions, cost of ownership, and vehicle survivability does not yield a full understanding of fleet-wide fuel consumption. Optimal vehicle choices from a LCOD standpoint may vary, depending on differing use cases. It is likely that a subset of consumers will find new technologies practical before they are useful to the whole market; for example, a battery electric vehicle (EV) driven more intensively than the average may have an easier time reaching cost parity than a "typical" vehicle.

This project addresses these analytical shortcomings resulting from assumptions of average, homogenous vehicle usage. Detailed understanding of vehicle travel at a disaggregated level is necessary to quantify important metrics more accurately. This project will assess variations in light-duty vehicle travel and registrations based upon real-world data to better estimate energy consumption, consumer costs, lifecycle emissions, and vehicle survivability.

Objectives

This project aims to understand what key metrics are changed, and how they are changed, by variations in light-duty vehicle usage. In particular, this project (1) quantifies variations in vehicle miles traveled (VMT), considering vintage, vehicle characteristics, and demographic characteristics; (2) quantifies LCOD for vehicles with different use intensities; (3) estimates the impacts of variations in VMT on 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 lengths of time that different types of vehicles stay on the road. These results will be broadly shared to better inform calculations by the U.S. Department of Energy (DOE) and others.

When considering specific fleets, knowledge of operational behavior is necessary to determine fleet purchasing decisions. In 2021, President Biden signed two Executive Orders encouraging the production and sale of zero-emission vehicles, including for plug-in EVs [1], [2]. Executive Order 14057 requires 100% purchases of zero-emission vehicles within the federally owned fleet by 2035. To achieve this goal, cost comparisons must be made between conventional and zero-emission vehicles. One high-profile fleet not covered by Executive Order 14057 is the United States Postal Service (USPS). However, the Inflation Reduction Act realizes the importance of the postal fleet and allocated $3 billion to ease electrification of the fleet, including money for vehicle purchases and for EV charging infrastructure [3]. This project will perform analysis in support of that mission, quantifying costs of operation with either gasoline or electricity, and highlighting locations that are particularly suited for vehicle electrification.

Approach

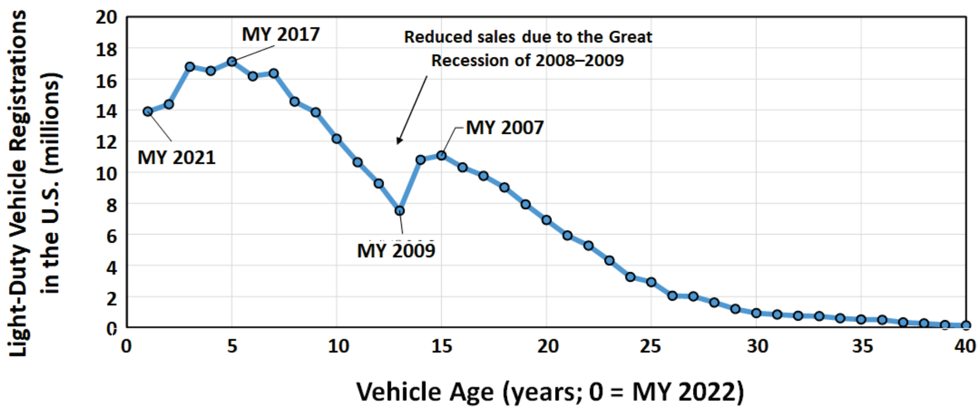
This project explores the non-homogeneous driving behavior of passenger and fleet vehicles, with the goal of better understanding representative user costs and the aggregate energy consumption of the light-duty vehicle fleet. The typical metric used for driving behavior is VMT. Since fuel consumption 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. In prior analysis, distributions of VMT from the National Household Travel Survey were examined as a function of multiple parameters related to vehicle age, vehicle characteristics, and demographics [4]. Depreciation is another key cost [5]; understanding the typical usable lifetime of a vehicle is necessary to quantify annual depreciation and to determine how much total fuel is consumed.

In this project, LCOD is the metric used to assess costs of different vehicle technologies for different driving habits, focusing on usage relevant for large fleets with heterogeneous usage patterns. LCOD calculations will focus on vehicle purchase costs and fuel costs and will include other costs (such as vehicle maintenance and repair), following the methodology developed in previous work sponsored by VTO [6]. For higher VMT, fuel costs will be a larger portion of the total cost. For EVs, these fuel costs also include the costs borne out of installing charging infrastructure.

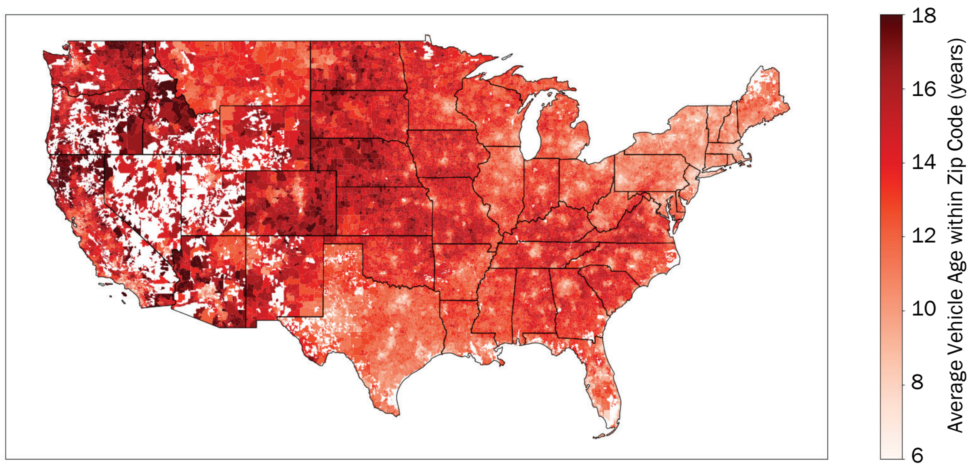
To determine operational behavior of vehicles, this project uses registration data for light-duty vehicles by Experian Automotive from initial sale until scrappage [7]. Earlier in the project, these registration data were compared with original vehicle sales, while current analysis considers how registrations vary by demographic characteristics. In Fiscal Year (FY) 2022, this project considered where vehicles were registered as a function of age and compared the demographics of each zip code with vehicle ownership. The local demographics of each zip code (specifically based on taxable household income) were compared with the average age of each vehicle to identify communities with older vehicles (which tend to have worse fuel economy and higher emissions). Income data came from estimates from the Census Bureau, from the American Community Survey at the Zip Code Tabulation Area level [8]. The U.S. Department of Housing and Urban Development has published a dataset for the relative degree of urbanicity for each census tract in the United States [9].

Results

Examination of vehicle registration data shows that there is a broad distribution in vehicle age, as shown in Figure V.1.1(a). Slightly more than half of the total vehicle registrations are for vehicles manufactured in the last ten years (model years [MY] 2012–2021). Vehicles of 1 or 2 years of age are moderately less common, owing to reduced vehicle sales during the COVID-19 pandemic. There is a notable decrease in vehicles between 10 and 15 years old (particularly MY 2009 and MY 2010) because of the reduced sales of the Great Recession of 2008–2009. Beyond that, there is a gradual decrease in vehicle registrations with age, as older vehicles are scrapped and removed from service. However, this vehicle age distribution is not uniform across the country, as shown on the map in Figure V.1.1(b). In general, urban areas have a lower average vehicle age than rural areas. This is especially visible in several Great Lakes metropolitan areas; Nashville, Tennessee; Atlanta, Georgia; and the Texas Triangle. Interestingly, there are some locations with visible differences across state lines, e.g., Montana and Texas have newer vehicles than the surrounding states, and Virginia and Kentucky have older vehicles than their northern neighbors. Prior analysis in this project showed that this may be partially caused by variations in vehicle registration regulations, including requirements for vehicle inspections.



(a)



(b)

Figure V.1.1 (a) Distribution of vehicle ages of light-duty vehicles and (b) map of average age for light-duty vehicles in the United States. Source: Experian Automotive for December 2021 [7]

To assess the relative share of vehicles as a function of vehicle age and zip code income, the 31,727 zip codes with vehicle registrations are aggregated by percentile into 100 groups of approximately 317. For each zip code group, the total number of vehicles of each vintage is normalized by the total population. These data are presented as a heat map in Figure V.1.2. The number of vehicles per household of each vintage is plotted on the horizontal axis (newer vehicles on the left), and the vertical axis represents the zip code income percentile (high-income zip codes on the top). The color-axis represents the fraction of all vehicles, with brighter points representing groups with higher numbers of total registrations. This graphic shows that higher-income zip codes tend to have newer vehicles, and older vehicles diffuse through to lower-income locations. This is shown by a subtle diagonal trend leading away from the top-left corner (interrupted by the reduced sales in the Great Recession of 2008–2009). Figure V.1.2 also shows a band of vehicles from 14–18 years old that becomes more pronounced with reduced income. Secondly, higher-income neighborhoods also tend to have more vehicles than lower-income neighborhoods, especially for vehicles up to about 8 years old (MY 2014 and newer).

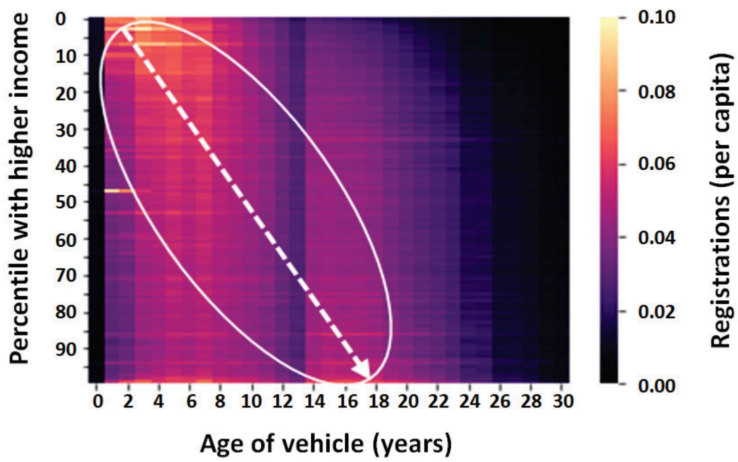
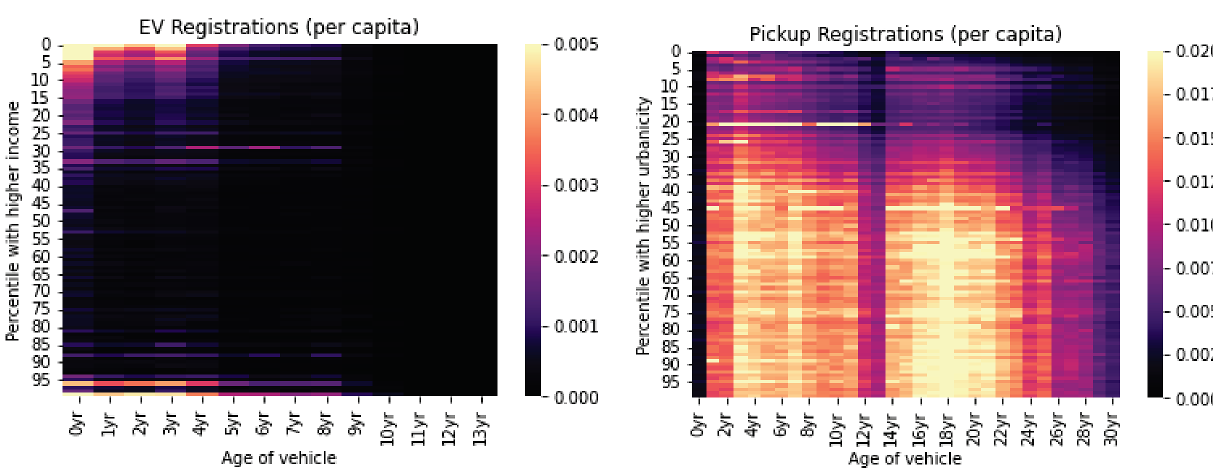


Figure V.1.2 Heat map of vehicle registrations by zip code as a function of vehicle age and average household income. Source: Argonne National Laboratory

Figure V.1.3 shows similar type of analysis for EVs and pickup trucks. For EVs shown in Figure V.1.3(a), there is a drastically different diffusion profile. EV registrations are primarily in the wealthiest third of zip codes. However, the newest vehicles (MY 2022, and to a lesser extent MY 2018–2021) are more diffused to medium-income communities than older EVs. While these vehicles have almost no penetration in zip codes below the median, there is a higher uptake of these vehicles in modestly wealthy neighborhoods, which may indicate that new EVs are becoming more affordable. For pickup trucks shown in Figure V.1.3(b), zip codes are instead binned by their urbanicity, where the vertical axis represents zip codes binned and ranked by the U.S. Department of Housing and Urban Development urban perceptions index (more urban zip codes on the top, more rural zip codes on the bottom). In this case, pickup trucks are predominately rural vehicles. The highest density for new purchases comes from vehicles near the median of urbanicity, typically suburban communities. Older models (e.g., 14–22 years old) are distributed across rural communities.



(a) (b)

Figure V.1.3 (a) Heat map of light-duty EV registrations as a function of vehicle age and average household income and (b) heat map of pickup truck registrations as a function of vehicle age and zip code urbanicity. Source: Argonne National Laboratory

A similar type of analysis shows that there may be proximity effects between vehicle manufacturing and vehicle sales. Nissan has domestic automotive plants only in the Southeast (Tennessee and Mississippi).

Analysis shows an abundance of cars registered within zip codes that are among the 10% closest to one of the three Nissan manufacturing plants in the United States (320 km). A similar analysis for General Motors (GM) shows little correspondence with car sales; however, GM manufacturing plants are more broadly distributed across the country.

Regarding federal fleets, this project has begun analysis of the vehicle usage of the USPS. There are over 35,000 postal facilities in the United States and territories (25,435 leased and 9,686 owned). For purposes of analysis, each of these post offices were used as a base with over 238,000 "routes" split between "city", "rural", and "highway contract" routes as defined by the USPS. These routes have wide variance in their operation. Figure V.1.4 shows histograms of their route lengths as extracted from the USPS webpage [10], which are used as a proxy for delivery vehicle travel. Most routes are less than 30 miles per day, but while city routes rarely exceed this length, rural routes commonly exceed 50 miles per day.

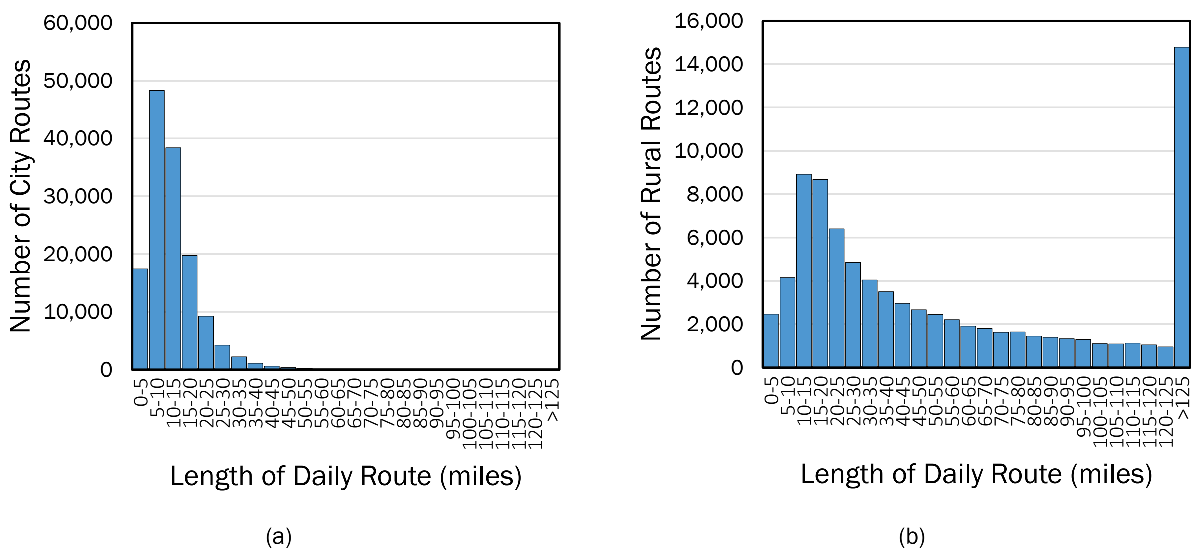


Figure V.1.4 Histogram of route lengths, grouped by (a) "city" and (b) "rural" routes. Source: Argonne National Laboratory

Because the USPS has operations across the country, local variations in costs are important to consider. Historically, gasoline prices have had greater temporal and spatial variability than electricity rates. Coupled with the greater efficiency of EVs, this leads to lower per-mile operating costs for EVs than conventional gasoline-fueled vehicles. The exact specifications of the Next-Generation Delivery Vehicle have not yet been made public, specifically, the incremental purchase cost for the EV relative to the gasoline vehicle. Funding from the Inflation Reduction Act may be able to offset much of this additional cost.

Conclusions

This project has found broad distributions in vehicle travel and vehicle ownership, 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, as vehicles are typically operated by multiple owners throughout their workable lifetimes. Higher-income zip codes tend to have newer vehicles, and older vehicles diffuse through to lower-income locations. EVs are particularly prominent in high-income zip codes.

Data from this task are used to quantify vehicle total cost of ownership and energy consumption based on inputs from parallel DOE-sponsored research. As described above, vehicle lifetime and typical annual travel are key assumptions that affect total cost of ownership and LCOD calculations. Continued work in FY 2023 will explore the operational side of federal fleets, including USPS, in more detail.

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Acknowledgements

Student researchers in the Science Undergraduate Laboratory Internship and Community College Internship programs have assisted with data processing and analysis, supported by the DOE Office of Science's Office of Workforce Development for Teachers and Scientists, namely Rebecca Schwartz, Calista Courtney, Emir Elzein, and Matthews Cribioli. Nazib Siddique of Argonne National Laboratory assisted with data analysis. Ken Kelly, Cabell Hodge, and Mark Singer of the National Renewable Energy Laboratory collaborated on work for delivery fleet analysis.

V.2 Transportation Macroeconomic Accounting Models: VISION and Non-Light Duty Energy and Greenhouse Gas (GHG) Emissions Accounting Tool (NEAT) (Argonne National Laboratory/National Renewable Energy Laboratory)

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Start Date: October 1, 2020 End Date: September 30, 2022
Project Funding: $250,000 DOE share: $250,000 Non-DOE share: $0

Project Introduction

Energy use by the U.S. transportation sector has significant impacts on national energy security and both pollutant and GHG emissions. To help research and develop technologies that can play a role in reducing those impacts, the 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 under different transportation decarbonization strategies at both the national and regional levels. The macroeconomic accounting models, VISION and the Non-Light Duty Energy and Greenhouse Gas Emissions Accounting Tool (NEAT), have been developed and supported by VTO to provide estimates of the potential energy use, oil use, and carbon emission impacts of advanced light-duty vehicles (LDVs), medium-duty vehicles (MDVs), heavy-duty vehicles (HDVs), all freight modes, and alternative fuels. [1], [2] The five freight modes are: (1) intercity freight-carrying trucks, (2) freight rail, (3) domestic freight marine, (4) domestic freight aviation, and (5) pipeline.

The VISION/NEAT models have over 8,000 users worldwide. The models are extensively used by the U.S. Department of Energy / Energy Efficiency and Renewable Energy (DOE/EERE) programs and other agencies in projects such as the VTO Analysis program, Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility, H2@Scale, and the EERE Strategic Analysis Decarbonization Analysis, to evaluate the impacts of advanced vehicle/fuel technologies. VISION/NEAT was recently used in the decarbonization tool development funded by EERE Strategic Analysis and will continue contributing to the cross-sectional decarbonization analysis. The NEAT model is also funded by Advanced Research Projects Agency - Energy (ARPA-E) to extend the fuel pathways (e.g., electricity and hydrogen) for rail decarbonization. Furthermore, the models are widely used by researchers in universities, state agencies, consultancies, and energy companies. Several states, such as California and New York, adopted the VISION/NEAT model structure and developed their state-level accounting tools based on this structure.

This project (1) annually updates and calibrates the VISION/NEAT models with projections from the Energy Information Administration's (EIA) Annual Energy Outlook (AEO) reference case and the Department of

Transportation's Freight Analysis Framework [3], [4], (2) enhances the medium- and heavy-duty (MDHD) modeling capabilities and adds heterogeneity to the model by adding flexible inputs for new mobility patterns and demographic variation that were developed in Fiscal Year (FY) 2021, and (3) conducts scenario analysis to assess the regional carbon emissions of electric vehicles adoption in the United States, considering the variation in the grid mix, work that was developed in FY 2022)

Objectives

The objective of this project has been 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. Enhanced MDHD capabilities and model heterogeneity both respond to the needs of benefits analyses and reflect the expanding DOE research and development portfolio in the MDHD and non-road sectors. These enhancements will also reflect emerging trends, such as the growth observed in local and regional shipping relative to long haul, and will support the future incorporation of emerging technologies, such as shared vehicles, as well as connected and automated commercial vehicles. Using the VISION model, this project also quantifies county-level emissions benefits from Plug-in Electric Vehicle (PEV) adoption and shows how regional variation depends on vehicle use and electric grid GHG emissions.

Approach

VISION/NEAT covers over ten on-road and off-road vehicle classes and over 20 different powertrain technologies. Figure V.2.1 shows the overall model framework, along with the vehicle technologies and transportation fuel pathways considered.

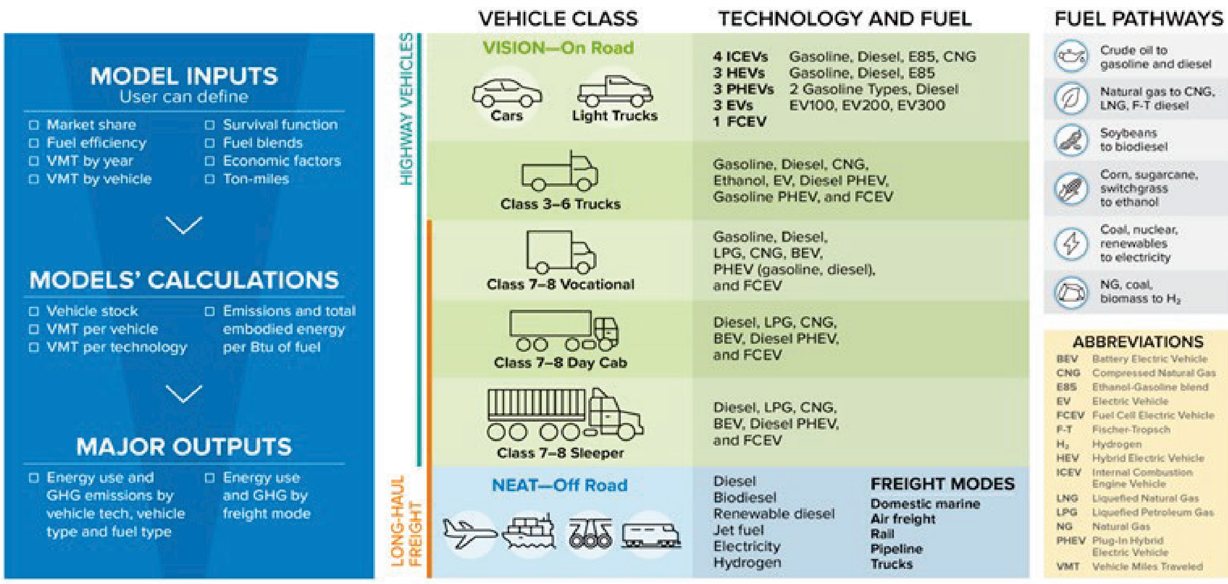

Figure V.2.1 VISION/NEAT model structure (VISION focuses on highway vehicle technologies; NEAT focuses on freight modes). Source: Argonne National Laboratory

Using the updated VISION model, we estimated the regional emissions benefits of PEV adoption. The emissions benefits of PEV adoption vary geographically, and factors that affect the actual magnitude of emissions benefits tend to vary even within a state. Additionally, the difficulty of acquiring local traffic data makes it very challenging to quantify the distributed impact of PEV adoption at finer geographic scales. This analysis demonstrated an approach to quantifying the potential emissions benefits from PEV adoption at the county level and explored factors causing the differences across regions using the process shown in Figure V.2.2. County-level vehicle emissions depend on county-level vehicle miles traveled (VMT), which have traditionally been difficult to measure. Vehicles registered in one county travel to adjacent counties regularly.

Therefore, the approach of extrapolating regional VMT from vehicle registrations is not sufficient to estimate the total VMT by county, which includes the VMT from vehicles registered in adjacent counties. This study estimated the county-level GHG emissions reduction that will occur with increased PEV adoption using actual on-road vehicle activities rather than vehicle registrations to account for traffic flows across counties. This study also considered the impact of existing state targets, such as zero-emission vehicle (ZEV) targets, for vehicle electrification. Matching the federal targets from the Biden Administration, this analysis assumed that 50% of new LDVs sold in the United States in 2030 will be PEVs. [5]

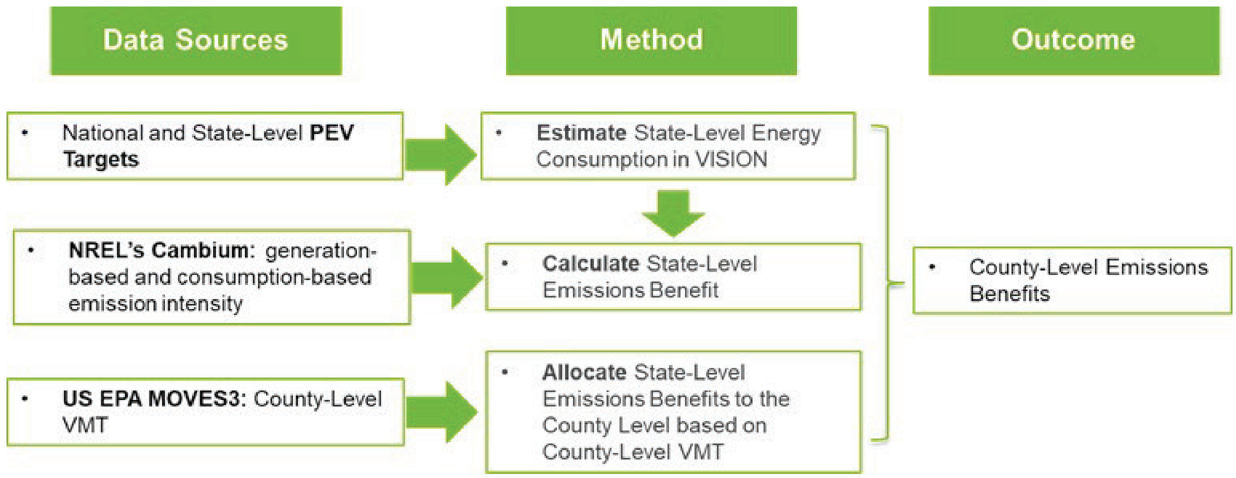

Figure V.2.2 Method for quantifying the distributed emissions impact of EV adoption and usage. Source: Argonne National Laboratory

Results

The VISION 2022 base case reflects projections relating to light and heavy highway vehicles in EIA's AEO 2022. [3] In the 2022 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. [6] GREET GHG coefficients account for the full fuel cycle. VISION 2022 has been updated to reflect the (1) EIA AEO 2022 Reference Case, and (2) GHG and upstream energy rates from GREET1_2022. Class 7-8 heavy-duty vehicles now are subdivided into three market segments with separate accounting for multiple powertrains technologies: vocational single-unit trucks and day cab (regional) tractor-trailer combination trucks. [7]

Figure V.2.3 shows the percentage of scenario emissions reduction compared with emissions under the base case PEV market shares from 2020 to 2050. The plot is divided into two groups (ZEV states vs. non-ZEV states) and three decades (the 2020s, 2030s, and 2040s). [8] Both ZEV and non-ZEV states expect to see emissions reduction in the next three decades. As PEV market shares increase, emissions reduction will also increase over the years. From the 2020s to the 2040s, non-ZEV states' median percentages of emissions reduction increase from 0.6% to 30.3% relative to the base case. For ZEV states, median percentages of reduction are much higher due to high projected PEV adoption goals and relatively clean grid mixes, increasing from 15.1% to 69.4% from the 2020s to the 2040s. As a result of differences in electrical grid mixes, the variation in emissions reduction across states becomes more substantial as PEV market shares increase.

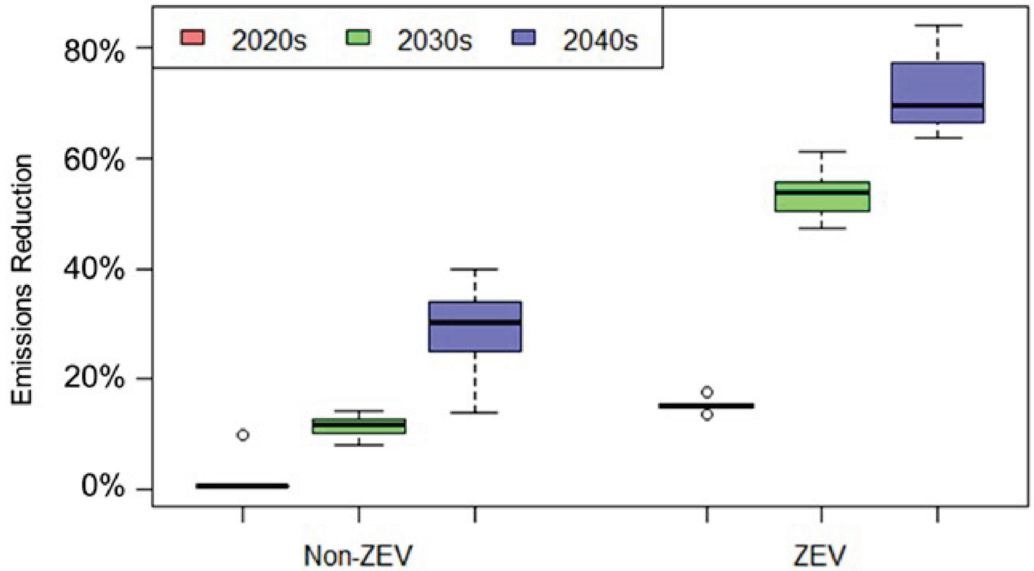

Figure V.2.3 Ranges for emissions reduction between non-ZEV and ZEV states from 2020– 2050 (The top and bottom of each bar represent the 25th and 75th percentile of emissions reduction rates by state. The line in the middle indicates the median. The top and bottom whiskers represent the maximum and minimum emissions reduction rates). Source: Argonne National Laboratory

We calculated cumulative emissions benefits from 2020 to 2050 for all counties in the lower 48 states, as shown in Figure V.2.4. [9] In general, because of the relatively aggressive goal of adopting PEVs, ZEV states, such as California and Colorado, tend to have larger emissions benefits than non-ZEV states. Nevertheless, despite the lack of ZEV mandates, states with large amounts of vehicle activity (e.g., Florida) have the potential to see substantial emissions benefits. Likewise, the most populated metropolitan areas of each state also have higher emissions benefits than other regions of the state due to high traffic volumes (e.g., Chicago, Illinois and the Twin Cities, Minnesota).

In contrast, many regions show limited potential for emissions reduction. First, some of the least populated states do not see large amounts of emissions benefits, even with increasing PEVs replacing gasoline vehicles (e.g., North Dakota). Moreover, regions with less clean electric grid mixes tend to have less potential for emissions reduction. For example, some parts of Indiana and Kentucky have high shares of coal being used in electricity generation, which leads to high carbon emissions intensities and less potential for emissions reduction. Los Angeles County, California, has the largest cumulative emissions reduction (170.3 million metric tons of carbon equivalent (MMTCe)), thanks to its relatively clean grid and large VMT volume. In contrast, Robertson County, Kentucky, has the lowest reduction (0.0 MMTCe), mainly due to the county's dependence on coal for electricity generation. At the state level, California has the largest cumulative emissions reduction (686.8 MMTCe from 2020-2050), and Wyoming has the smallest (2.5 MMTCe from 2020-2050).

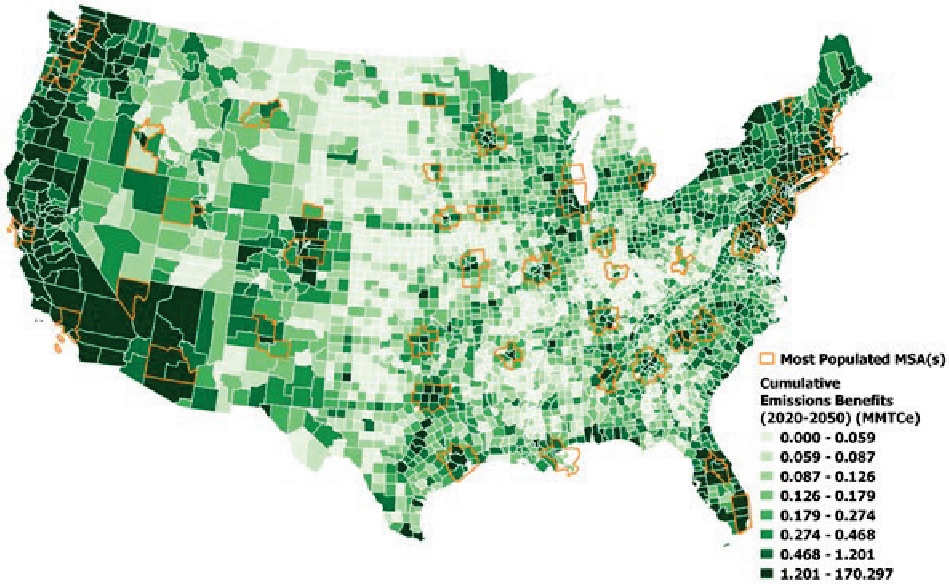

Figure V.2.4 Cumulative emissions benefits of PEV adoption in the lower 48 states compared to the base case PEV market share (2020–2050). Source: Argonne National Laboratory

Conclusions

The VISION/NEAT models have been used in several DOE/EERE programs and activities such as the VTO Analysis program, Transportation Decarbonization Analysis, SMART Mobility, and H2@Scale, to evaluate the impacts of advanced vehicle technologies. VISION/NEAT has over 8,000 users.

In this project, Argonne's VISION/NEAT model was fully updated to match the projections in the EIA AEO 2022 Reference Case. VISION/NEAT is also updated with GHG and upstream energy rates from GREET1_2022. Historical vehicle sales, stock, fuel economy, and other data were collected and documented in the model.

County-level emissions analysis shows that the adoption of PEVs will have nationwide emissions benefits with significant regional variation. For non-ZEV states, median percentages of emissions reduction could increase from 0.6% to 30.3% over the next three decades. In comparison, ZEV states have higher median rates of emissions reduction, increasing from 15.1% to 69.4% over the next three decades. PEV adoption goals, electric grid mixes, and vehicle activities all affect the magnitude of achievable emissions reduction and lead to geographic variations in emissions benefits across counties. The cumulative emissions benefits range from 170.3 MMTCe (Los Angeles County, California) to 0.0 MMTCe (Robertson County, Kentucky).

Key Publications

1. Gohlke, D., Kelly, J., Stephens, T., Wu, X., Zhou, Y. 2022. "Mitigation of emissions and energy consumption due to light-duty vehicle size increases". Transportation Research Part D: Transport and Environment, Volume 114, 2023, https://doi.org/10.1016/j.trd.2022.103543.

2. Wu, X., Zhou, Y., Gohlke, D., Kelly, J. 2023. "Light-Duty Plug-In Electric Vehicle Adoption: County-Level Emissions Benefits, accepted for oral presentation at the 2023 Transportation Research Board Annual Meeting, Washington D.C., 2023.

References

1. Argonne National Laboratory VISION model. https://www.anl.gov/es/vision-model

2. Argonne National Laboratory NEAT model. https://www.anl.gov/es/neat-nonlight-duty-energy-and-ghg-emissions-accounting-tool

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4. Federal Highway Administration, Freight Analysis Framework, https://faf.ornl.gov/faf4/Default.aspx

5. The White House. FACT SHEET: President Biden Announces Steps to Drive American Leadership Forward on Clean Cars and Trucks. https://www.whitehouse.gov/briefing-room/statements-releases/2021/08/05/fact-sheet-president-biden-announces-steps-to-drive-american-leadership-forward-on-clean-cars-and-trucks/. Accessed April 07, 2022.

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9. National Renewable Energy Laboratory, 2021. Cambium Documentation: Version 2021. https://www.nrel.gov/docs/fy22osti/81611.pdf. Accessed November 16, 2021.

Acknowledgements

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VI Integrated Analysis

VI.1 GREET Life Cycle Analysis (Argonne National Laboratory)

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Start Date: October 1, 2019	End Date: September 30, 2022	
Project Funding (FY22): $500,000	DOE share: $500,000	Non-DOE share: $0
Project Funding (FY20-FY21): $350,000	DOE share: $350,000	Non-DOE share: $0
Total Expected Project Funding: $850,000	DOE share: $850,000	Non-DOE share: $0

The GREET® (Greenhouse gases, Regulated Emissions, and Energy use in Technologies) model is an instrumental tool for life cycle analysis (LCA) supported by U.S. Department of Energy (DOE) since 1994. It is updated and released to the public annually with its two different frameworks (Excel and .Net versions) that reflect the state-of-the-art fuel and vehicle technologies, and emerging LCA issues. The model benefits from the deep technical analysis that is supported within this project and GREET is used within the project to support research tasks such as those of the Driving Research and Innovation for Vehicle Efficiency and Energy Sustainability (U.S. DRIVE) Integrated Systems Analysis Technical Team (ISATT) program, as well as important quick-turn analysis requests from the U.S. DOE.

VI.1.1 Expansion and Update of GREET2 Modeling and Capabilities

Task Introduction

This task examines automotive components and the production of critical materials used in them, spanning raw materials extraction and the processing of those raw materials into usable forms for vehicles. This is accomplished using a mix of LCA and supply chain analysis to (a) identify the hot spots along the supply chains of materials for energy use, greenhouse gas (GHG) emissions, and other environmental burdens; and (b) evaluate the up-to-date energy and environmental burdens of producing the concerned automotive components, and finally, the vehicle. LCA is needed to determine the energy and environmental burdens of producing automotive materials, and thereby the final automobile, while the supply chain analysis is critical to incorporating supply chain-related factors in calculating environmental burdens (e.g., ore type and technologies used for material production, as well as local energy input parameters). For this analysis, Argonne configured the GREET® model to reflect: (a) updated production inventory for aluminum (Al), copper (Cu), and rare-earth elements (REEs), accounting for their domestic and imported sourcing; and (b) updated bill-of-materials (BOMs) for traction motor, electronic controller, and hydrogen tank storage systems (HTSSs) of light-duty vehicles (LDVs) and medium- and heavy-duty vehicles (MHDVs) with hybrid (conventional, plug-in), electric, and fuel-cell powertrains.

Objectives

The goals of this task are to: (a) enhance the supply chains and production inventory of critical materials pivotal for advanced vehicle powertrains within GREET to update their energy and environmental burden; and (b) update the material composition of components used in advanced powertrains to provide an accurate reflection of their production-related environmental burdens. Three critical materials – Al, Cu, and REEs – and three automotive components – traction motor, electronic controller, and HTSSs – were covered in this task. Steel and Al were used as initial examples to understand the effect of the method used for end-of-life (EOL) burden accounting (recycled content vs. EOL displacement credit) for all vehicles.

Approach

For critical materials, Argonne updated the supply chains (to reflect their current supply mix to the United States) and production inventory (material and energy inputs and process emission outputs for all steps, spanning mining to final processing) in GREET. For all materials, these updates reflect their domestic production and imports from various sources. Additionally, for Cu, the updates account for its production from various ore types (sulfide and laterite) and across varying ore grades (% Cu content) for sulfide ores. These updates enable a better understanding of the effect of regional supply chain factors (such as ore type and technology used for material production, transportation modes and distances involved, and local energy input parameters) on the environmental burdens of material production. Further, Argonne investigated the BOMs of traction motors and electronic controllers for hybrid, electric, and fuel-cell powertrains of all vehicles (light/medium/heavy-duty) as a function of peak power and voltage requirements per literature [1], [2], [3], [4], and of HTSSs for fuel-cell powertrains of MHDVs per data from Strategic Analysis, Inc. [5].

Results

In fiscal year (FY) 2022, Argonne updated its life-cycle inventory (LCI) within GREET for Al, Cu, and REEs, along with the BOMs for traction motor, electronic controller, and HTSSs of vehicles spanning different weight classes and powertrains. For Al, we updated its production pathway and associated LCI to reflect its supply chain at different levels of products (alumina, Al smelting, primary Al ingot, and semi-fabricated Al products). For Cu, we updated its production pathway and LCI to account for its obtainment from ores of different types (sulfide/laterite) and spanning various grades. We also compare the relative differences in the environmental performance of Cu from sulfide and laterite ores and compare those against those of nickel (Ni) (also updated this year), given the similarity in their ore types and processing methods. We also introduced a new pathway for REEs production from both bastnasite/monazite ores and ion adsorption clays and provided their corresponding LCIs. Additionally, we revised the BOM of (a) the traction motor and electronic controller for hybrid (conventional and plug-in), electric, and fuel-cell powertrain-fueled light-, medium-, and heavy-duty vehicles, allowing for variation in their BOM as a function of peak power and voltage characteristics; and (b) HTSSs for MHDVs based on fuel-cell powertrain.

Previously, Argonne conducted an updated LCI for Al production in various forms (primary, secondary, and three semi-fabricated products: extruded, sheet, and cast Al. Al is used extensively in vehicles of different weight classes in wrought and cast forms, and its use is expected to rise further with time to achieve the objective of vehicular lightweighting by replacing steel [6], [7]. This is expected to increase vehicle-cycle environmental and energy burdens due to Al's higher contributions on both counts compared to steel [6]. The United States is also becoming more reliant on imports to meet its primary Al needs since the last LCI update [7], which affects its environmental burden and that of subsequent products (secondary/recycled Al and semi-fabricated products). To account for the aforementioned aspects, in FY 2022, Argonne updated production pathways and corresponding LCIs for Al ingots (primary and secondary) and six semi-fabricated products (automotive Al – extruded and sheet; non-automotive Al – extruded, sheet, and foil; and cast Al). The supply chains and LCIs are based on data from the Aluminum Association 2022 report [7], considering North American (NA) production and imports in GREET as adequately representing reliable supply chain needs for the United States.

About one-fifth of NA primary Al demand is met via imports, while the remaining domestic share (81%) is produced using a NA electric grid mix (for Al smelting) and a U.S. grid mix (for other steps) as shown in Figure VI.1.1.1(a) [7]. For primary Al ingot, sourcing plays an influential role in GHG burden of Al production shown in Figure VI.1.1.1(b), causing a jump of ~10% on shifting from NA production mix to NA consumption mix (domestic production + imports) as shown in Figure VI.1.1.1(b). The major contributors to these burdens are alumina production (via substantial use of coal and natural gas) and its subsequent electrolysis (biggest contributing step due to its large use of electricity). The consequential GHG burdens of semi-fabricated Al products (on a per-pound basis) are provided in Table VI.1.1. 1. Overall, the results highlight the need for greater use of (a) renewable energy for primary Al ingot production, especially for the Hall-Heroult process; and (b) secondary (recycled) Al in production of semi-fabricated products to lower their resultant GHG intensity.

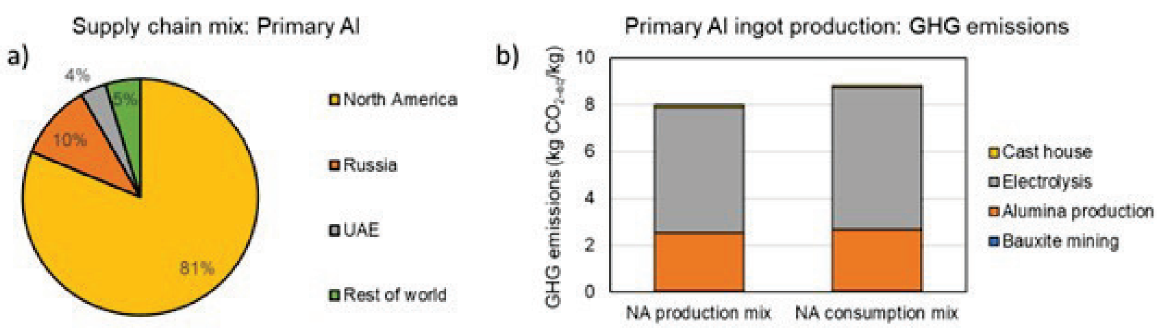


Figure VI.1.1.1 (a) Share of different sources in total primary Al supply to North America (based on [7]); and (b) GHG burdens of primary Al ingot based on GREET simulation (NA production mix: primary Al production in North America; NA consumption mix: primary Al consumed in North America). Source: Argonne National Laboratory

Table VI.1.1.1 GHG Burdens of Semi-Fabricated Al Products Based on GREET Simulation

Forms of Al		GHG emissions (kg CO2-eq/kg)
Automotive Al	Extruded	5.7
	Sheet	11.8
Non-Automotive Al	Extruded	7.0
	Sheet	5.3
	Foil	6.1
Cast Al		3.2

Cu is an important constituent of automotive components in conventional and advanced powertrains, such as engines, lithium-ion batteries, motors, and controllers. It is produced from sulfide and laterite (oxide) ores that are located in different nations and that show a wide range of ore grades (% element content). Previous GREET versions provided a single, individual LCI for Cu production as representative of all ore types, grades, and sources. However, Cu's ever-rising use has increased its mining, causing: (a) a major decline in its ore grade over time, which increases its production-related environmental burden; and (b) a shift in its production from sulfide ores towards laterite ores [8], [9], [10].

In FY 2022, Argonne provided separate, independent production pathways and corresponding LCIs for sulfide and laterite ore-based Cu production. The United States produce the bulk amount of its Cu needs, with Canada and Chile being the dominant import sources as shown in Figure VI.1.1.2. We updated the material and energy inputs for Cu production from both ores, accounting for the shares of different nations in the respective supply chain. Our GREET simulations show lateritic Cu production to have lower GHG intensity than sulfidic Cu production. This is the exact converse of our GREET simulation results for production of Ni - another element updated in GREET in FY 2022, as shown in Figure VI.1.1.3. Given the similarities between Ni and Cu in terms of their ore types (sulfide and oxide) and processing treatments used for their production (pyrometallurgy and hydrometallurgy), lateritic Cu is expected to be more GHG-intensive than sulfidic Cu. The contrarian nature of our results likely is the consequence of the reduced amount of details available for material and energy inputs used for lateritic Cu production. These findings also highlight the need for use of alternative, less energy-intensive technologies to produce these elements, and judicious use of Cu reserves via various means, including by adopting appropriate recycling techniques.

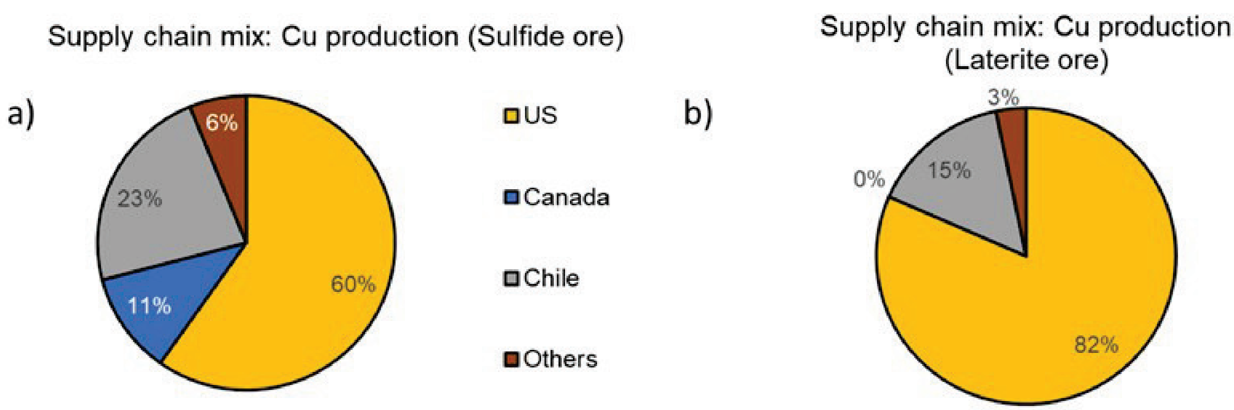


Figure VI.1.1.2 GHG burdens associated with producing: (a) nickel and (b) copper from sulfide and laterite ores (based on GREET simulation). Source: Argonne National Laboratory

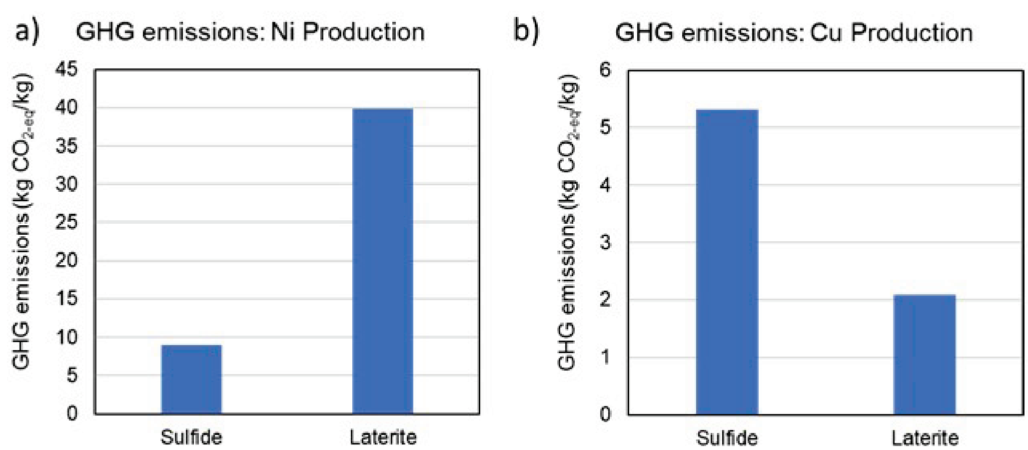


Figure VI.1.1.3 Supply chain mix for (a) Ni production and (b) Cu production based on [11]. Source: Argonne National Laboratory

Previous GREET versions provided a very brief understanding of the actual production steps and corresponding LCIs for REEs production. However, the use of REEs has only expanded across the domain to include automotive components like traction motors (magnets) and nickel-metal hydride batteries, technologies meant to produce alternative automobile fuels like hydrogen (solid oxide electrolyzers), and for distribution of electricity produced using renewables. In FY 2022, Argonne incorporated an exhaustive set of production steps and associated LCIs for REE production in China – the biggest global producer – based on its two main ore types: (a) bastnasite and/or monazite ores that are the main source of light and medium REEs; and (b) ion adsorption clays that are the main source of heavy REEs with sufficient amounts of light and medium REEs [12], [13]. Bastnasite/monazite (B/M) ores are the dominant ore type for production of REEs, but their negligible content of heavy REEs makes ion adsorption clays the main source of these heavy REEs. REEs are produced in a series of steps that can be divided into two stages: (1) production of rare earth oxides (REOs) from mined ore and (2) subsequent reduction of REOs to REEs. Production of REOs from B/M ores has a higher GHG burden than its counterpart based on ion adsorption clays, mainly due to the much higher contributions from the solvent extraction step for B/M ores through its higher use of energy and from use of specific intermediate materials as shown in Figure VI.1.1.4 [12]. For REEs, the references used provide multiple pathways to produce individual elements like lanthanum and praseodymium, along with their corresponding LCIs. All the production pathways are incorporated in GREET, with users having the option to choose among them and obtain the resultant GHG and other environmental burdens for each production pathway.

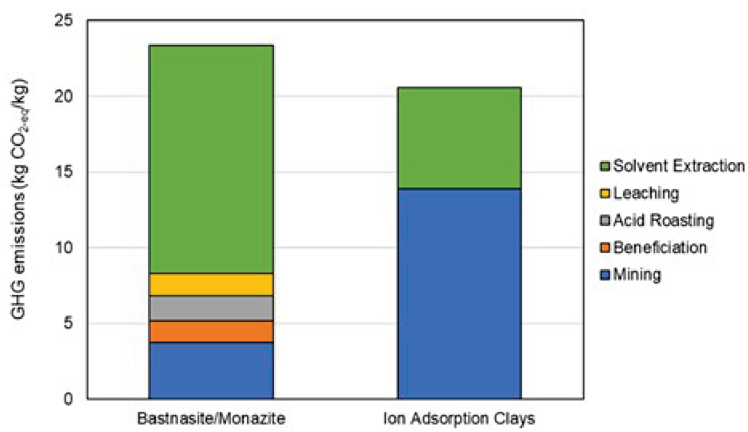


Figure VI.1.1.4 GHG emissions for REO production from different ore types (based on GREET simulation). Source: Argonne National Laboratory

For electric drive components (traction motor and electronic controller), previous GREET versions used BOMs obtained from a teardown study on LDVs for hybrid, electric, and fuel-cell powertrains, and extended these to MHDVs due to lack of alternative data. These BOMs assume a standard mix of steel, cast Al, Cu, rubber, and plastics but do not consider the use of magnets in motors and other materials like ceramics, mica, phenolic and epoxy resins, zinc, and fiberglass. In FY 2022, Argonne updated the BOMs for these components as a function of their peak power and voltage values for LDVs and MHDVs of concerned powertrains based on the literature [1], [2], [3], [4]. For conventional hybrid and fuel-cell powertrains, the BOMs vary with the desired power for the considered vehicle, and for plug-in hybrid and electric powertrains, the variation of BOMs with vehicle range is accountable. The updated BOMs enable a more accurate and holistic determination of energy use and environmental burdens associated with the production of electric drive components, and thereby, of the final vehicle. Additionally, for fuel-cell powertrains of MHDVs, we updated the BOM of HTSSs, based on the input from Strategic Analysis, Inc. of Al being the material used for housing hydrogen tanks instead of stainless steel [5]. This has a major bearing on both the HTSSs weight and resultant manufacturing-related GHG burdens, given that Al is both lighter in weight and more GHG-intensive than stainless steel.

Across all LCIs, a key feature is the development of inventories for intermediate materials used to produce the final material which would be a composition of Al/Cu/REE. Comprehensive LCIs were developed for these intermediate materials, and we used these to enable accurate determination of various environmental burdens for production of different elements.

Conclusions

This task updated the production pathways and LCIs for critical materials and key components for vehicles, towards enabling an accurate and holistic determination of their environmental burdens. GHG burdens for Cu production highlighted the need to develop alternative processing techniques for production with lower GHG intensity. The analysis for Al highlighted the need for increased use of renewable energy to reduce environmental burdens of primary Al production, as well as higher use of secondary (recycled) Al for producing semi-fabricated products to reduce their respective GHG intensity. The incorporation of REEs production LCI in GREET enables a more comprehensive understanding of contributions from various processing steps on different environmental burdens. The updates to various vehicle components further the cause of accurate evaluation of energy use and environmental burdens associated with their production, as well as the vehicle cycle of various vehicles considered in GREET.

Key Publications

1. Iyer, R.K. and J.C. Kelly. 2022. "Updates on Inventory of Aluminum Production," Argonne National Laboratory publications. https://greet.es.anl.gov/publication-alum_update_2022.

2. Iyer, R.K. and J.C. Kelly. 2022. "Updates to Vehicle-Cycle Inventory for Select Components of Light-Duty, Medium-Duty, and Heavy-Duty Vehicles," Argonne National Laboratory publications. https://greet.es.anl.gov/publication-ldv_mhdv_updates_2022.

3. Iyer, R.K. and J.C. Kelly. 2022. "Life-Cycle Inventory of Critical Materials: Nickel, Copper, Titanium, and Rare-Earth Elements", Argonne National Laboratory, ANL/ESIA-22/8. https://greet.es.anl.gov/publication-critical_mat_2022

VI.1.2 Update and Evaluation of Consumption and Generation-Based U.S. Electricity Grid Modeling

Task Introduction

Accurate inventories of emissions from transportation-related point sources are important for regional life-cycle environmental impact analysis of vehicle technology options such as BEVs and petroleum-fueled internal combustion engine vehicles (ICEVs). In FY 2022, Argonne developed detailed GHGs and criteria air pollutants (CAPs) emission inventories for power plants in 2020 and refineries in 2019 at the facility level in the United States. The newly developed power plant emission datasets from 2020 were further used in an integrated modeling framework that was developed in previous FYs to characterize the consumption-based electricity characteristics at the regional level in the U.S. In particular, in FY 2022, Argonne did a systematic upgrade of this electric grid modeling framework to cover the whole North and Central American connected electric networks and collected and processed additional electricity sales data to expand the consumption-based analysis to the monthly and end-use sectoral levels for each state.

Objectives

The objectives of this task were to (1) develop detailed emission inventories of power plants and refineries in the United States at the facility level for both GHGs (including CO_2, CH_4, and N_2O) and CAPs (including NO_x, SO_2, CO, volatile organic compounds, particulate matter (PM_{10}, $PM_{2.5}$), black carbon, and organic carbon), (2) upgrade integrated electric grid modeling framework to cover all electricity interchanges among balancing authorities (BAs or BA equivalents) in North and Central American connected power grids, and (3) derive electricity characteristics to include mixes, energy use intensities, and emission intensities of GHGs and CAPs for individual states by end-use sector and by month.

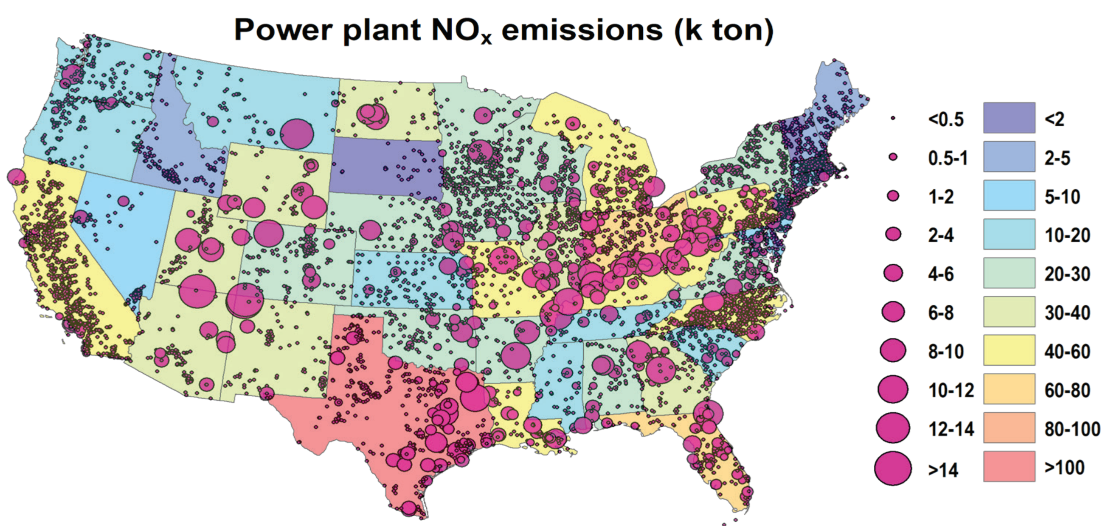
Approach

For power plants in the United States, emissions of CO_2, CH_4, and N_2O were calculated as the product of the plant-level total energy consumption by energy source from the U.S. Energy Information Administration (EIA) Form-923 and the energy-source-specific emission factors from the U.S. Environmental Protection Agency (EPA) Emissions and Generation Resource Integrated Database. NO_x and SO_2 emissions by power plant were from the actual emissions data collected by EPA's Continuous Emissions Monitoring System. For other CAPs, we carefully reviewed and manually matched EIA's electricity generation data and EPA's 2017 National Emission Inventory (NEI) data at the facility level, estimated the emissions of NEI-unreported plants, and scaled up to 2020 based on plants' total energy consumption changes from 2017 to 2020. For petroleum refineries, facility-level GHG and CAP emission inventories were based on careful matching of EPA's Greenhouse Gas Reporting Program and the 2017 National Emission Inventory. CAP emission estimates were scaled up to the year 2019 based on the crude throughput changes of individual refineries from 2017 to 2019.

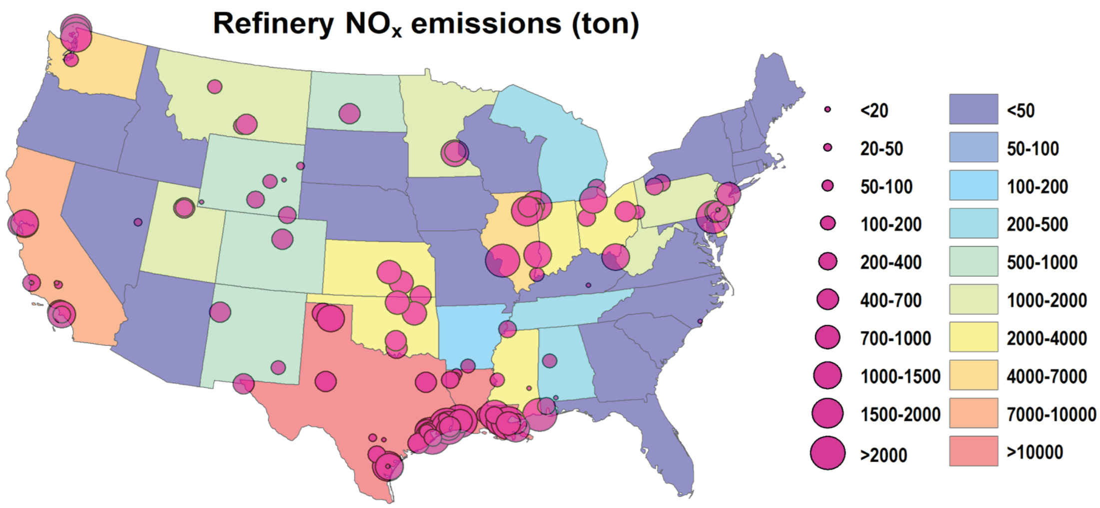
Argonne did a systematic upgrade of the regional consumption-based electric grid modeling framework in GREET to cover not only the United States, Canada, and Mexico, but also seven Central American countries whose networks are indirectly connected to the U.S. network through the Mexican grid. Besides the newly developed U.S. power plant emission datasets, Argonne collected, processed, and estimated all relevant data at the BA or BA equivalent and the monthly levels in 2020 for all countries including electricity generation, fuel consumption, electricity imports and exports among BAs or BA equivalents, GHG emissions, CAP emissions, electricity sales, and transmission losses. In particular, monthly electricity sales data were processed to obtain state-level electricity sales matrices by BA and by end-use sector in the United States. With Argonne's GREET.Net software, the above-mentioned data were incorporated into the upgraded electric grid modeling framework to derive consumption-based electricity characteristics at the monthly and end-use sectoral levels for each state.

Results

Argonne developed facility-level GHG and CAP emission inventories for more than 10,000 power plants in 2020 and 130 petroleum refineries in the United States in 2019. Figure VI.1.2.1(a) shows examples of spatial distributions of NO_x emissions from power plants and Figure VI.1.2.1(b) for refineries. Results are available for other CAPs and individual GHGs. The total CO_2, CH_4, N_2O, volatile organic compounds, CO, NO_x, SO_2, particulate matter (PM_{10}, $PM_{2.5}$), black carbon, and organic carbon emissions attributed to electricity generation in U.S. power plants in 2020 were estimated to be 1.62×10^6, 100, 18.4, 29.6, 447, 1.12×10^3, 859, 118, 95.9, 5.42, and 19.4 thousand tons, respectively. For refineries, they were estimated to be 2.16×10^5, 11.3, 1.82, 17.8, 47.9, 87.0, 27.6, 23.0, 20.0, 2.43, and 3.30 thousand tons, respectively, in 2019.



(a)



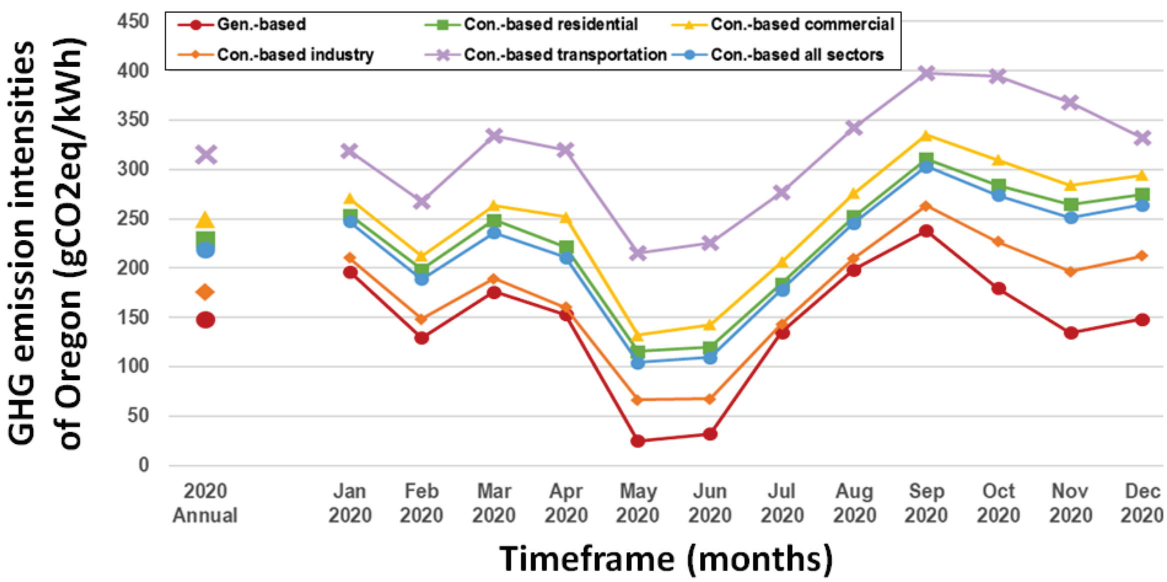
(b)

Figure VI.1.2.1 (a) NO_x emissions from power plants and (b) petroleum refineries in the United States. The size of circles indicates the facility emissions, and the color of states demonstrates the state emissions. Source: Argonne National Laboratory

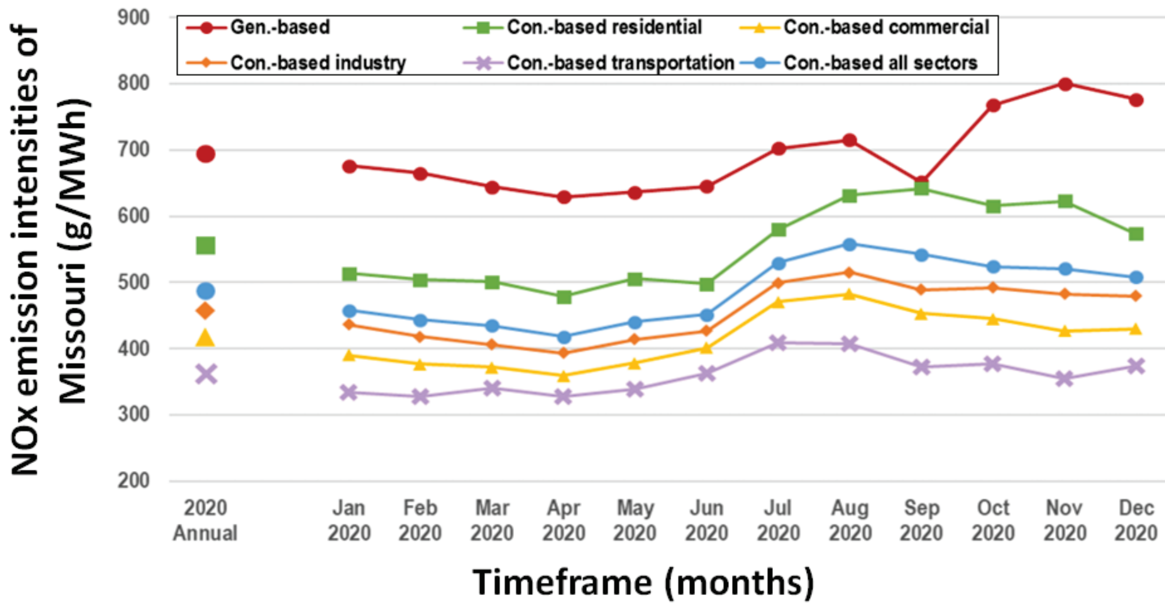
Because there are frequent electricity interchanges among regions in the whole of the North and Central American power grid, regional electricity characteristics as derived from a consumption-based perspective are expected to differ from those characterized solely based on electricity generation. As in the past, our results in FY 2022 show that consumption-based electricity characteristics differ significantly from generation-based characteristics for most regions in North and Central America. There were only three states with a shift of electricity mixes less than 5 percentage points and 39 states with a shift of mixes larger than 15 percentage points in 2020. About 9.3% of GHG emissions and 6%–11% of CAP emissions (depending on the species) from power plants in North and Central America were embedded in electricity interchanges and transferred inter-regionally.

Regional electricity characteristics also show significant seasonal and end-use sectoral variations. Figure VI.1.2.2(a) shows examples of monthly variations of electricity GHG intensities in Oregon and Figure VI.1.2.2(b) shows NO_x intensities in Missouri at the wall outlets by end-use sector in 2020. Similar results for electricity mixes, energy use intensities, and emission intensities of individual GHGs and CAPs for all states are also available.

At the national level, electricity emission intensities are relatively high in summer and winter and low in spring and autumn. Nationally, electricity used in the industry sector is generally more GHG- and CAP-intensive than that used in the other end-use sectors. For example, GHG, SO_2, and NO_x emission intensities of electricity consumed in the industry sector were 6.0%, 13.5%, and 6.4% higher than the average of all-sector electricity use, respectively. However, these electricity characteristics are very state-dependent as evidenced by the monthly and sectoral emission intensity variations of Oregon and Missouri shown in Figure VI.1.2.2. Also note that the electricity used in the transportation sector does not include electricity that is charged to on-road plug-in electric vehicles but includes electricity that is used in railroads and railways. Therefore, for technologies that consume a large amount of electricity, their life-cycle energy and environmental impact evaluation could have significant regional, temporal, and sectoral variations.



(a)



(b)

Figure VI.1.2.2 (a) Monthly variations of electricity GHG emission intensities in Oregon and (b) NO_x emission intensities in Missouri at the wall outlets in 2020 for generation-based results and consumption-based results by end-use sector. Source: Argonne National Laboratory

Conclusions

Argonne developed facility-level emission inventories of GHGs and CAPs for the power plants and refineries in the United States which provide detailed emission characterization of the U.S. power industry and petroleum refining industry at regional levels. The previously developed integrated electric grid modeling framework for consumption-based regional electricity characterization was systematically upgraded to cover not only the United States, Canada, and Mexico, but also seven Central American countries that are indirectly connected to the U.S. power grid. The updated consumption-based electricity database improves the representation of regional, seasonal, and sectoral electricity in the whole of the North and Central American power grid.

Key Publications

1. Ankathi, S., Lu, Z., Zaimes, G., Hawkins, T., Gan, Y., Wang, M. 2022. "Greenhouse gas emissions from the global transportation of crude oil: current status and mitigation potential". *Journal of Industrial Ecology*. doi:10.1111/jiec.13262

2. Burnham, A., Lu, Z., Wang, M., Elgowainy, A. 2021. "Regional emissions analysis of light-duty battery electric vehicles". *Atmosphere,* 12(11), 1482. doi:10.3390/atmos12111482

3. Lu, Z., Elgowainy, A. "Regional electricity characteristics of North and Central American electric network". In preparation.

VI.1.3 Integrated Systems Analysis Technology Team (ISATT) Analysis of Vehicle/Fuel Systems

Task Introduction

This task uses LCA to estimate the cradle-to-grave (C2G) GHG emissions and costs of LDVs and MHDVs considering current and future technologies. For this analysis, Argonne configured the GREET® model to evaluate the lifecycle GHG emissions of current and future technology pathways of petroleum and renewable gasoline for ICEVs and hybrid electric vehicles (HEVs), conventional and renewable natural gas for compressed natural gas ICEVs, diesel for ICEVs, corn and cellulosic ethanol for ICEVs, steam-methane reforming (SMR) and renewable hydrogen for fuel cell electric vehicles (FCEVs), and current and low carbon electricity for plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). Cost data were obtained from the literature and DOE modeling for both current and future vehicle powertrain and fuel conditions. This task builds from prior efforts in the area. In particular, the LDV study serves as an update to a 2016 study with a similar scope.

Objectives

The goal of this task is to identify the C2G GHG emissions and costs associated with current (2020) and future (2030-2035) LDV and MHDV technologies while considering a variety of different fuel pathways. The study in 2022 is focused on the finding of the LDV analysis [15]. 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 have been identified that offer both significant GHG reductions as well as cost reductions.

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 EOL decommissioning and recycling of vehicle components. All LCA calculations were performed using the GREET model with modifications to fueling pathways and vehicle parameters based on C2G specifications. The cost analysis considered the costs 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 were obtained from agency projections such as those by the EIA, literature, modeling for both current and future conditions.

The fuel pathways considered in this study are shown in Table VI.1.3.1. The selected fuel pathways were constrained to those deemed to be nationally scalable in the future. Unless otherwise specified, all cases assume large scale for both fuel and vehicle technologies (i.e., high production volume is assumed unless explicitly specified). The electricity mix used in stationary processes in FUTURE TECHNOLOGY pathways comes from the 2035 U.S. grid generation mix projected by the EIA Annual Energy Outlook (AEO) 2021 [15] unless otherwise specified.

Table VI.1.3.1 Fuel Production Pathways Considered in This C2G Analysis

Fuel	CURRENT TECHNOLOGY CASE	FUTURE TECHNOLOGY CASE
Gasoline (E10)	U.S. average crude mix (blended with 10% corn ethanol)	Pyrolysis of forest residue (no ethanol blending)
		E-fuels (Nuclear electricity + CO_2)
		E-fuels (Renewable electricity + CO_2)
Diesel	U.S. average crude mix	Bio-renewable diesel (pyrolysis of forest residue)
		Hydroprocessed renewable diesel from soybeans
		20% fatty acid methyl ester drop-in bio-based diesel, B20, from soybeans[a]
		Gas-to-liquid Fischer-Tropsch diesel
		E-fuels (Nuclear electricity + CO_2)
		E-fuels (Renewable electricity + CO_2)
Compressed Natural Gas	U.S. average of conventional and shale gas mix	Renewable natural gas from landfills
Ethanol (E85)	85% corn ethanol (blended with 15% petroleum gasoline blendstock)	85% cellulosic from corn stover (blended with 15% petroleum gasoline blendstock)
Hydrogen	Centralized production from SMR of natural gas	Low temperature electrolysis from wind/solar power
		High-temperature electrolysis using nuclear energy
		Natural gas SMR with carbon capture and storage
Electricity	EIA-AEO U.S. average electricity generation mix in 2020	Natural Gas advanced combined cycle
		Wind power
		Solar photovoltaic power

[a] American Society for Testing and Material (ASTM) specifications for conventional diesel fuel (ASTM D975) allows for biodiesel concentrations of up to 5% (B5) to be called diesel fuel (ASTM 2010). B20 (20% biodiesel, 80% petroleum diesel) is a biodiesel blend available in the United States that represents the maximum allowable concentration of biodiesel in ASTM D7467. The fatty acid methyl ester is also known as biodiesel. Percentage blending values are by volume.

Vehicle fuel economies and component sizes were estimated using Argonne's vehicle simulation tool, Autonomie, for a consistent set of vehicle performance criteria across vehicle-fuel combinations. Each vehicle is presumed to be optimized for the fuel on which it operates. Inputs to Autonomie were based on vehicle manufacturers' information and assumptions made by the authors, along with specific technology assumptions provided by the DOE Vehicle Technology Office and the Hydrogen Fuel Cell Technologies Office, which reflect vehicle performance improvements that are in line with targets set by these DOE offices for advanced vehicles. All vehicle platforms were evaluated using standard EPA regulatory drive cycles, the Urban Dynamometer Driving Schedule and the Highway Fuel Economy Test. Vehicles modeled in Autonomie met the following criteria: (1) vehicle acceleration from 0 to 60 mph in 8 s (±0.1 s), (2) gradeability of 6% at 65 mph at gross vehicle weight, and (3) maximum vehicle speed ≥100 mph [16].

The component sizes and vehicle fuel economy results were incorporated into the 2020 version of the GREET model to evaluate GHG emissions of vehicle production ("GREET2" model) and fuel cycles ("GREET1" model), respectively. Meanwhile, a range of future vehicle cost estimates (with vehicles modeled in 5-year time steps) were developed based on a range of technology progress (more optimistic and less optimistic), resulting in a low- to high-cost range, and these vehicle costs were used to evaluate the life cycle cost of driving.

The case presented here is the high powertrain technology progression pathway with the central cost cases for each fuel.

Results

By far the largest and the most consequential change in the input assumptions between the prior study and this current update is in battery costs for BEVs. The past 5-10 years have seen dramatic reductions in the cost of EV batteries while, similarly, battery cost projections have also changed significantly over the past five years.

Figure VI.1.3.1 represents a sub-set of the study results. The figure demonstrates that, for the gasoline ICEV small SUV, potential vehicle efficiency gains would bring emissions down from 429 g CO_2e/mi indicated by the black line representing CURRENT TECHNOLOGY to 322 g CO_2e/mi indicated by the red line showing GHG emissions reductions in a FUTURE TECHNOLOGY case resulting from such potential future vehicle efficiency gains. These emissions could be further reduced using a low-carbon fuel source to between 91 g and 52 g CO_2e/mi as represented by the endpoint of the grey arrows. We further see that the burden of vehicle production (indicated by the blue line representing the case where the vehicle is operated on a 0 g CO_2e/mi fuel) for the ICEV accounts for 40 g CO_2e/mi of the FUTURE TECHNOLOGY emissions. Note that these vehicle production emissions do not include potential emissions reduction technologies for future vehicle material production.

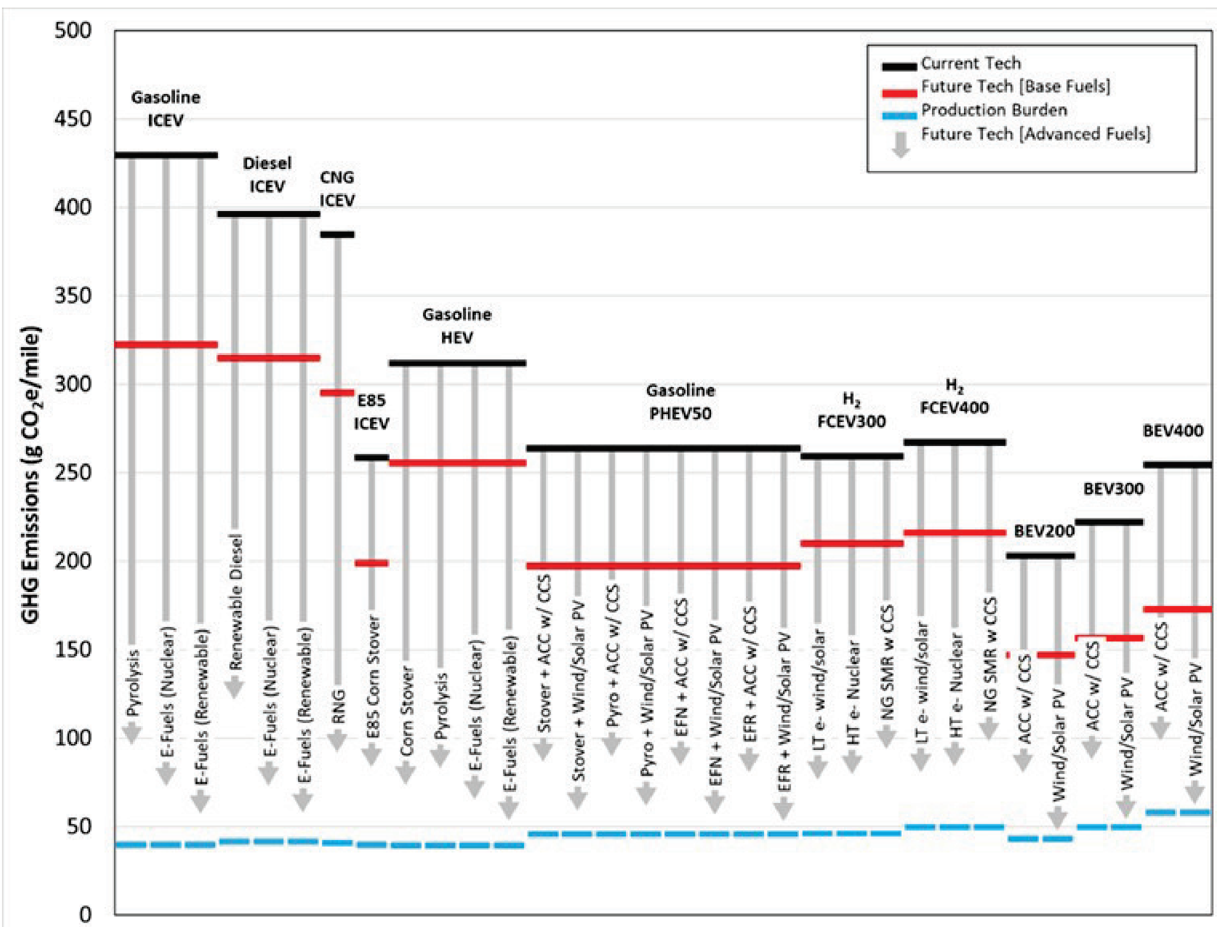


Figure VI.1.3.1 C2G GHG emissions of various vehicle-fuel pathways for small SUVs assuming high technology progress. Analysis was performed using GREET2020. Source: Argonne National Laboratory

Figure VI.1.3.1 also shows that, by combining vehicle efficiency gains with low-carbon fuels, GHG emission reductions more than double in most cases compared to vehicle gains alone. Note that the down-arrows show a plausible reduction of the carbon footprint of the vehicle-fuel pathway from low-carbon fuels and electricity, but the feasibility of achieving the indicated GHG emission reductions was not considered. More broadly, these results demonstrate that large GHG reductions for LDVs are challenging and require consideration of the entire life cycle including vehicle manufacture, fuel production, and vehicle operation.

To allow for comparison of the cost-effectiveness of potential emissions reductions across different strategies for GHG mitigation, a "cost of avoided GHG emissions" analysis is used. This analysis presents the total CO_2e emitted and total cost during the vehicle lifetime as a point on a two-dimensional plot. Additionally, the percent reduction in CO_2e from the gasoline ICEV is also presented for comparison.

The cost of avoided GHG emissions for the CURRENT TECHNOLOGY and FUTURE TECHNOLOGY cases for small SUVs is shown in Figure VI.1.3.2 and Figure VI.1.3.3. Total emissions, over the noted time frame, are shown on the primary x-axis, and percent reduction from the conventional gasoline vehicle on the secondary x--axis, while lifetime vehicle cost is shown on the y-axis. The results indicate opportunities for GHG reduction with all powertrains. While cost reductions are not observed for the CURRENT TECHNOLOGY case, we find that several FUTURE TECHNOLOGY cases offer both cost and emission reduction opportunities.

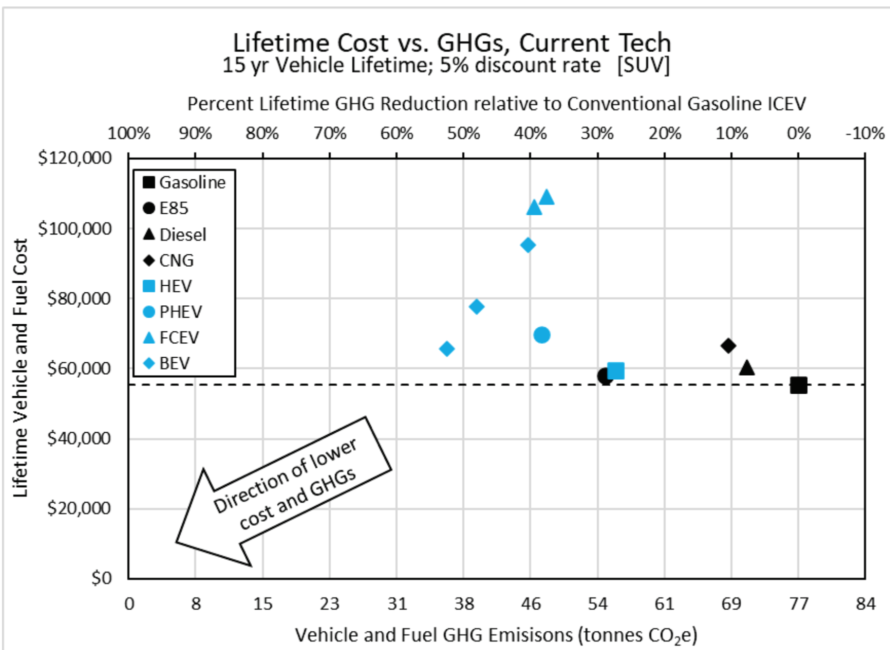


Figure VI.1.3.2 Lifetime costs versus GHG emissions by vehicle-fuel pathway for the CURRENT TECHNOLOGY case for small SUVs (2020$). Source: Argonne National Laboratory

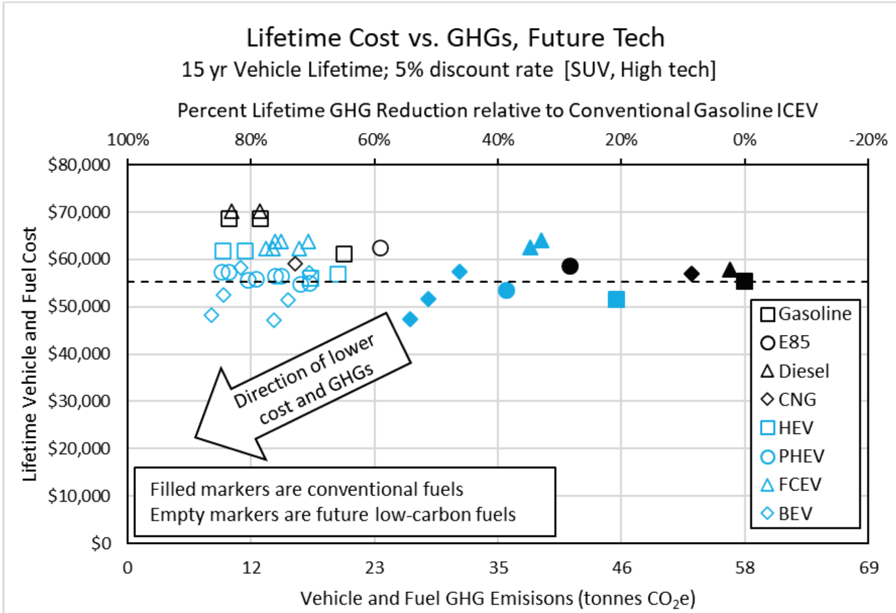


Figure VI.1.3.3 Lifetime cost versus GHG emissions by vehicle-fuel pathway for the FUTURE TECHNOLOGY case for small SUVs (2020$). Source: Argonne National Laboratory

The modeled costs of avoided GHG emissions for the majority of FUTURE TECHNOLOGY cases, considering the full 15-year vehicle lifetime, are below $200/tonne CO_2e with many options below zero (i.e., they cost less than the ICEV and emit fewer emissions).

For the FUTURE TECHNOLOGY case, HEV, plug-in hybrid electric vehicle, and BEV platforms offer the lowest modeled costs of avoided GHG emissions, with many options having a negative cost (i.e., the cost is less than that of the gasoline ICEV). The FCEVs offer lower-cost GHG emissions opportunities than the ICEV technologies, with the exception of the E85 vehicle operating on corn stover and the compressed natural gas vehicle operating on renewable natural gas.

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_2e contents. For the CURRENT TECHNOLOGY case, carbon abatement costs are generally on the order of $100s per tonne CO_2e to $1,000s per tonne CO_2e for alternative vehicle-fuel pathways compared to a conventional gasoline vehicle baseline. FUTURE TECHNOLOGY carbon abatement costs vary significantly by technology and fuel pathway with several pathways, mostly electric vehicle, which are below zero (i.e., there is a cost reduction for carbon abatement). The pathways that do have a carbon abatement cost are generally in the range $100–$1,000/tonne CO_2e.

Key Publications

1. Kelly, J. C.; Elgowainy, A.; Isaac, R.; Ward, J.; Islam, E.; Rousseau, A.; Sutherland, I.; Wallington, T. J.; Alexander, M.; Muratori, M.; Franklin, M.; Adams, J.; Rustagi, N. 2022. “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.” Argonne National Laboratory publication, ANL-22/27. https://greet.es.anl.gov/publication-c2g_lca_us_ldv

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VI.2 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 (FY22): $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 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 account for the wide 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 Vehicle Technologies Office (VTO) are then used to define energy consumption for different timeframes and under different scenarios.

During the first year of performance, this project focused on light-duty passenger vehicles and defined powertrain distributions that provide the lowest cost of driving. This analysis was extended to commercial vehicles during the second year of performance and included a study of the relationship between the penetration of plug-in electric vehicles and the number of available public charging stations. During the third year of performance, we narrowed the analysis to the Knoxville-Chattanooga-Atlanta corridor and studied the impact of freight electrification on the electric grid.

Objectives

The project objectives for FY 2022 were to (1) evaluate the benefits of electrifying last mile deliveries and regional freight in the Atlanta-Chattanooga region, and (2) estimate the associated electric demand on the grid.

Approach

For the freight modeling of the Atlanta region, the number of freight firms were used to estimate the number of depots. This included 13,000 businesses with Dun & Bradstreet numbers and an assumption was made that 20% of these have depots. This resulted in 2,446 depots distributed across 1,250 zones, with a fleet distribution based on Bureau of Transportation Statistics data. The freight model assumed that 32% of the trucks were in a fleet of less than 15 and 68% of the trucks were in a fleet of 15 or more. There were 13 million miles travelled daily for medium duty and heavy duty (MDHD) vehicles which included 265,000 medium duty (MD) tours and 71,000 heavy duty (HD) tours.

For the grid modeling, the electric grid system and data was extracted from the Eastern Interconnection of the U.S. Synthetic Grid (ACTIVSg70k), a 70,000 bus synthetic grid of the eastern United States. Filtered electrical nodes and lines were selected to represent the power grid model in the Atlanta-Chattanooga area. The Atlanta-Chattanooga grid model included 1,463 nodes, 1,728 transmission lines, 231 generators, 1,301 electricity demand nodes, 2,446 freight depots, and 25,389 MW of generation capacity.

Results

Freight Modeling and Truck Volumes

The POLARIS [1] regional transportation model developed as part of other DOE-funded projects was used as a baseline and was further developed to represent real freight conditions in the region, as shown in Figure VI.2.1. The model was calibrated using data from the Freight Analysis Framework. Again, the region is represented by 2,446 depots distributed across 1,250 zones, as shown in Figure VI.2.2. And, as indicated earlier, approximately one-third of trucks are in fleets of less than 15 vehicles, while the remaining trucks belong to fleets of 15 vehicles or more. Tours were then constructed using the Vehicle Inventory and Use Survey and truck telematics data. (Tours are made up of a succession of trips and start and end at the same location, with the last trip representing the return to the depot.) Tours were then fed into SVTrip [2] and Autonomie [3] to determine energy consumption.

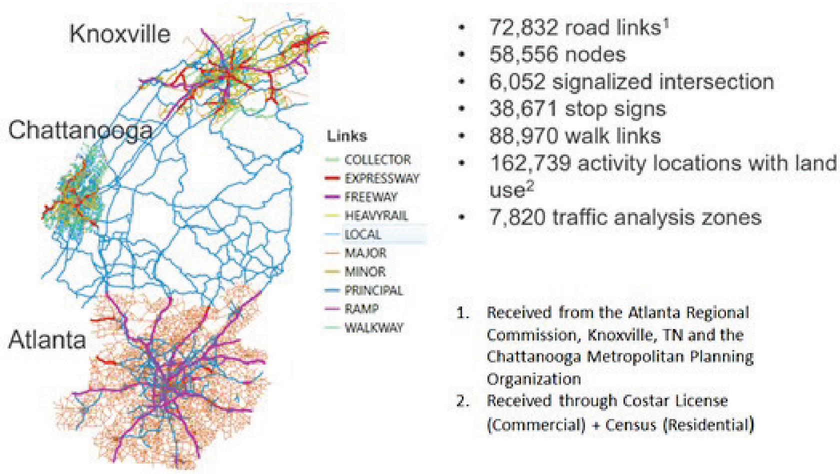

Figure VI.2.1 Network model for the region. Source: Argonne National Laboratory

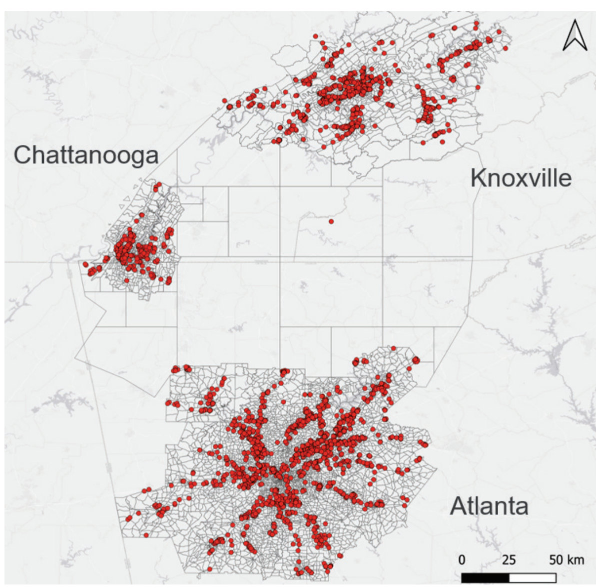

Figure VI.2.2 Depot location in Atlanta/Chattanooga/Knoxville region. Source: Argonne National Laboratory

Electricity Demand and Greenhouse-Gas Impact Based on VTO Targets

Greenhouse gases (GHGs) and electricity demand were calculated for light duty (LD) as well as MDHD vehicles for different combinations of timeframes and levels of technology achievement. Timeframes were defined as Current Term (CT), Short Term (ST), Medium Term (MT), and Long Term (LT). Technology levels were defined as "low" (representing limited or low levels of technology progress over time) and "high" (representing scenarios where VTO technology targets are met). Figure VI.2.3 shows electricity demand from battery electric vehicles (BEVs) and GHGs for all vehicles for different timeframes and technology levels. Electricity demand from LD vehicles far exceeds that of MDHD vehicles. However, while electricity demand from passenger cars is likely to be widely spread across the network, that of MDHD vehicles will be concentrated at the depots. Figure VI.2.3 also highlights the following details:

- The GHGs of LD vehicles reduces by a factor of 6 in the "LT high" scenario compared to the baseline, while, for MDHD vehicles, GHGs only reduce by half.
- As electrification increases, the well-to-tank portion of GHGs increases over time.
- In the baseline case, MDHD GHGs are approximately one third that of LD GHGs, while in the "LT high" case that proportion doubles to about two-thirds, so the share of MDHD GHGs increases over time.

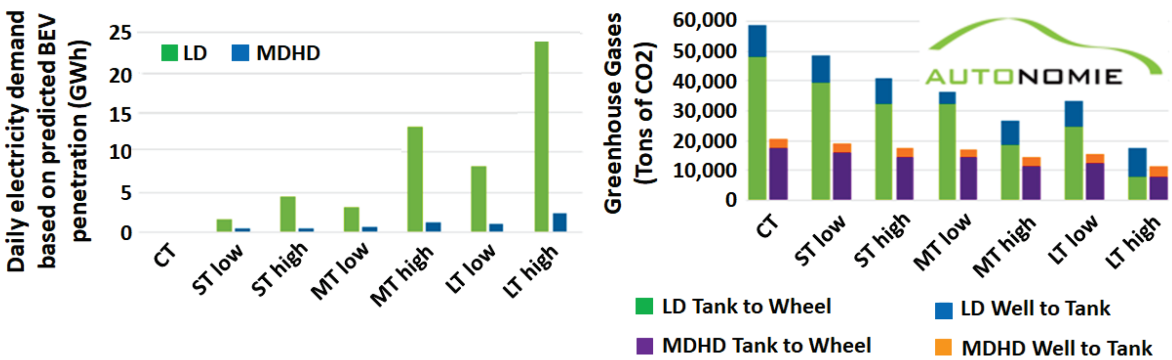

Figure VI.2.3 Electricity demand and GHGs. Source: Argonne National Laboratory

Cost of driving

Considering all MDHD vehicles, an aggregate levelized cost of driving (LCOD) was calculated. LCOD considers the purchase price of the vehicles as well as the energy-related costs (diesel and electricity). Figure VI.2.4 shows that, relative to the CT baseline:

- LCOD in "MT high" and "LT high" decreases. The increase in electrification and technology improvement are large enough to overcome the impact of an increased cost of diesel. (Figure VI.2.4)
- LCOD in "ST low" and "ST high" scenarios decreases. Diesel cost has not increased significantly, and technology progress allows for sufficient reduction in energy consumption to decrease LCOD. (Figure VI.2.4)
- LCOD in "MT low" and "LT low" scenarios increases due to a high share of internal combustion engine powertrains and an increase in diesel cost. (Figure VI.2.4)
- At the aggregate level, achieving VTO targets for MDHD trucks represents a 1% reduction in LCOD in the ST scenarios, a 6% reduction in the MT scenarios, and an 11% reduction in the LT scenarios. (Figure VI.2.4).

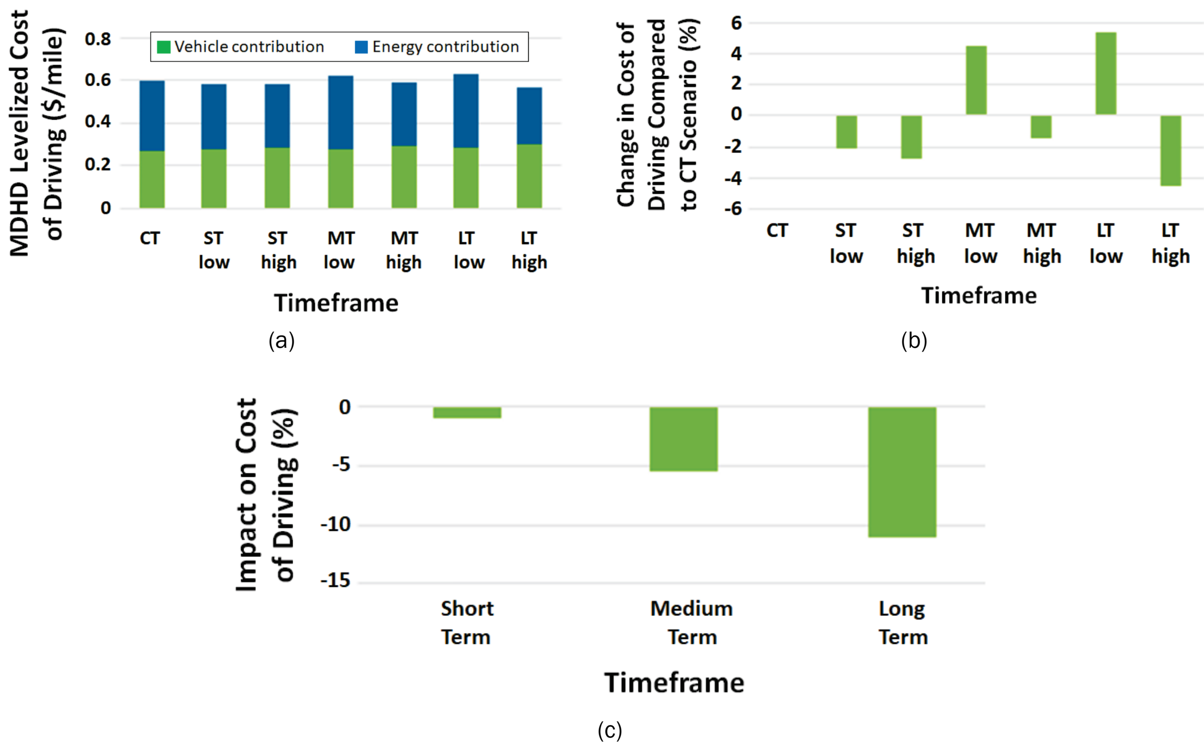

Figure VI.2.4 VTO technologies impact on the cost of driving – high versus low scenario – (a) MDHD LCOD, (b) Change in LCOD from baseline (CT), and (c) Intra-period (i.e., timeframe) LCOD impact of achieving VTO targets for MDHD trucks. Source: Argonne National Laboratory

Electric Grid Impact

A model of the grid for the region was built based on the ACTIVSg70k [4] model of the eastern U.S. electric grid. The electricity demand for July 1st was used to represent the baseline load. July 1st represents a day of high demand (though it is not the day with the highest demand of the year). The grid network was reduced to 120 nodes, and generators were added to represent the import of electricity from outside of the network. The covered area has a total peak demand of 27 GW. The existing generation capacity within the system is 20 GW, while the import capacity is 16.5 GW. This combines to give a total generation capacity of 36.5 GW (which assumes 35% reserve).

Figure VI.2.5 shows the daily electricity demand for the scenarios defined previously. In the figure, "Base" represents the baseline electricity demand to which the demand from vehicle electrification is added. An additional "Y2040" scenario has been added that considers the expected increase in travel demand in 2040 due to an increase in population (25% increase relative to 2020) and an increase in freight demand (37% increase relative to 2020 based on the Freight Analysis Framework data). In this initial analysis, the electricity demand from electrification is assumed to happen overnight and is equally distributed between 8 p.m. and 6 a.m.

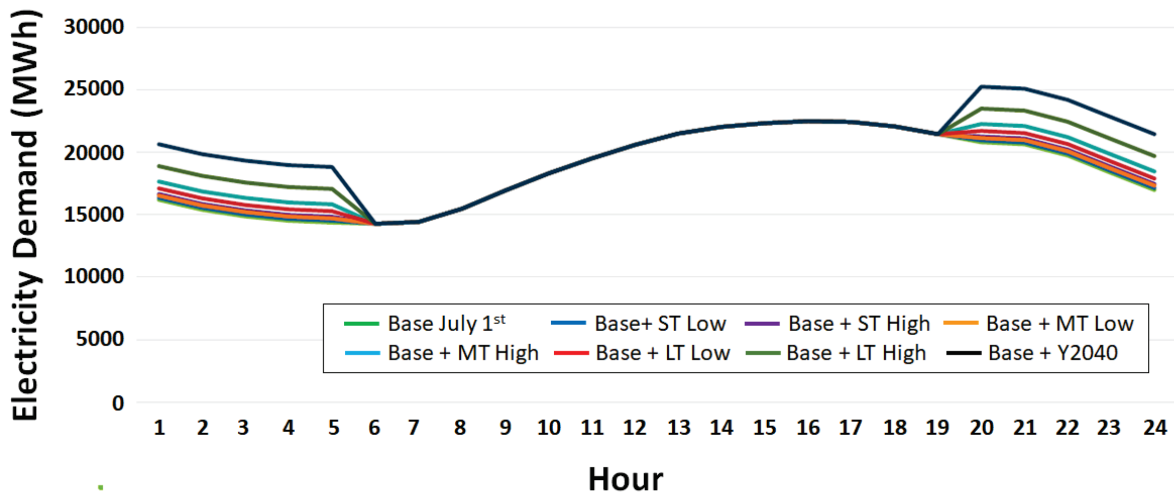

Figure VI.2.5 Electricity demand comparison for different EV adoption scenarios. Source: Argonne National Laboratory

Figure VI.2.6(a-b) shows that the impact on electrification with charging equally distributed overnight ("Before Adjustment") is null or small for all cases other than the 2040 case. Shifting charging away from the periods of high demand in the early evening hours when overall demand is high ("After Adjustment") allows for a increasing reduction in the average price as the level of electrification increases

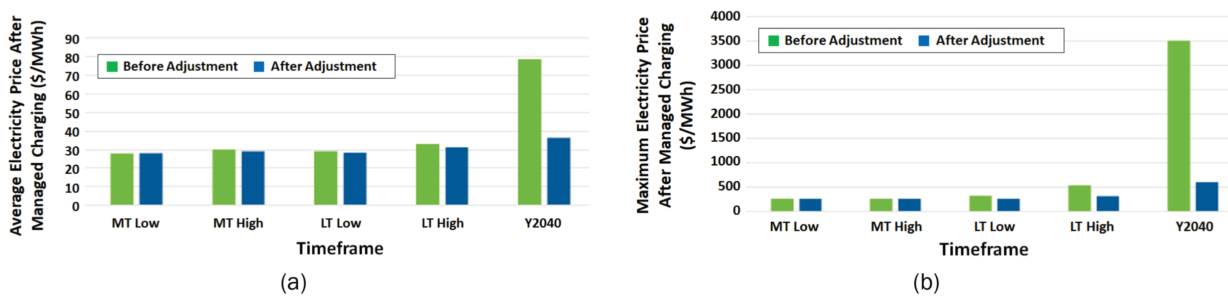

Figure VI.2.6 (a) Average and (b) maximum electricity prices. Source: Argonne National Laboratory

Conclusions

This analysis has shown the following:

- At the aggregate level, achieving VTO targets for MDHD trucks represents a 1% reduction in LCOD in the ST scenarios, a 6% reduction in the MT scenarios, and an 11% reduction in the LT scenarios.
- Without significant technology improvement (i.e., without meeting the VTO technology targets), the overall cost of driving could increase by 4% and 5% for the MT and LT scenarios, respectively, due to the expected increase in the cost of diesel.
- While vehicle electrification is not likely to create congestion on the grid in the near future, the expected high level of EV penetration as well as the increase in travel demand (from both passenger and commercial vehicles) can create congestion issues in longer-term scenarios if the grid capacity is not increased accordingly.
- Choosing the optimal time to charge (i.e., "smart charging") can have a significant impact on electricity price and grid congestion.

Future analysis could be undertaken to study how to best combine smart-charging schemes to limit electricity price hikes (i.e., optimization on the grid side) with the limitations of charging batteries at a high rate when the state of charge is high (i.e., optimization on the vehicle side).

Key Publications

1. Zhou, Zhi, Lusha Wang, Vincent Freyermuth, Natalia Zuniga-Garcia, Olcay Sahin, and Monique Stinson. 2022. "Grid and Market Impact from Transportation Electrification: A Case Study of Heavy-duty Freight Electrification in the Atlanta-Chattanooga Region." Slide presentation at the 2022 INFORMS Annual Meeting, Indianapolis, IN, October 16–19.

2. Zuniga-Garcia, Natalia, Vincent Freyermuth, Monique Stinson, and Olcay Sahin. 2023. "Impacts of Freight Fleet Electrification in the Atlanta – Chattanooga Region." IEEESusTech2023, Portland, Oregon, April 19-22, 2023, Accepted paper EDAS ID No. 1570869148. https://ieee-sustech.org/program/list-of-accepted-papers/

3. Zuniga-Garcia, Natalia, Vincent Freyermuth, Monique Stinson, and Olcay Sahin. 2023. "Impacts of Freight Fleet Electrification in the Atlanta – Chattanooga region." Paper presented at the 102nd Annual Meeting of the Transportation Research Board, Washington, DC, January 8–12.

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Acknowledgements

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VI.3 ACT Trucking States Analysis (Rocky Mountain Institute)

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Total Project Funding: $377,666	Total DOE share: $339,899	Total Non-DOE share: $37,767

Project Introduction

Over 500 million metric tons of equivalent carbon dioxide (CO_2e) are emitted annually by over-the-road freight movement in the United States [1]. These vehicles drive a collective 275 billion miles [2] and move 10 billion tons of freight annually [3]. From delivery vans to long-haul trucks, the environmental burden of moving goods contributes to local air pollution and global greenhouse gas emissions. Medium- and heavy-duty (MDHD) vehicle classes contribute about half as many greenhouse gas emissions as light-duty vehicles, however there are roughly 90% fewer on the road; therefore, MDHD vehicles have an outsize proportional contribution when compared to light duty.

Many of the technological advances that have led to electric passenger vehicles becoming more affordable, such as lower battery costs, have also led to breakthroughs in electric MDHD (eMDHD) vehicle production. Today, there are over 50 eMDHD vehicle models available in the United States [4], with many more scheduled for release in the coming years [5]. However, the anticipated benefits from electrifying the trucking sector rely on more than electric vehicle model availability. The charging infrastructure required to power these vehicles is also of critical importance. Compared to passenger vehicle charging infrastructure, eMDHD vehicles require more expensive chargers capable of delivering higher power, and therefore judicious planning of this infrastructure is crucial.

At a high level, the goal of this project is to identify the most easily "electrifiable" trucks in 15 states that have enacted freight electrification legislation and to quantify the charging energy and infrastructure required to power these vehicles.

Objectives

The objective of the project is to create an understanding of the charging infrastructure required to support the effective use of electric trucks in states that have committed to increasing the sales of those vehicles. The focus will be on first mover market segments and real-world data will be used to understand how charging needs are likely to be distributed over space and over time. This analysis will enable effective policymaking, fleet purchasing, and utility/public utility commission investment planning to provide a supportive operating environment for these vehicles. In addition to a final report, this work will develop a web-based, public-facing tool allowing users to explore the data at different levels of geographic aggregation.

Approach

During Budget Period 1, we analyzed trucking telematics data in the 15 states that are working toward implementing the Advanced Clean Trucks (ACT) rule [6] to understand how trucks currently operate and to identify electrifiable duty cycles using current electric truck technology. We then computed the energy needed to electrify these duty cycles and the necessary charging infrastructure under various scenarios. We have also begun to generate load profiles based on duty cycle and required charging energy.

Defining Electrifiability

We define electrifiable vehicles as those that return to a depot after fewer than 300 miles of travel in 95% of instances. These criteria—limited travel distance and a return to a fixed base—are intended to capture the two primary constraints on real-world operation of electric trucks: limited mileage range and lack of public and/or shared charging infrastructure. This definition of electrifiability aims to capture the segment of the trucking market most easily electrified in the next one to three years. On a longer time-horizon, electric truck ranges will likely increase, and public truck charging infrastructure may become more prevalent.

Telematics Data

We obtained trucking data from Geotab, a leading provider of telematics in North America. The telematics data that Geotab provided—collected for all days in calendar year 2019—are aggregated by vehicle class (medium-duty (MD) and heavy-duty (HD)), electrifiability, and county. The data schemas are shown in Table VI.3.1, Table VI.3.2, and Table VI.3.3. The data are from internal combustion engine trucks. However, the observed driving patterns of these vehicles can be used to determine which trucks could be replaced by electric vehicles based on existing electric vehicle technology and charging infrastructure.

Table VI.3.1 Geotab Telematics Information Provided in All Schemas

Variable Name	Value Type/Details
State	California, Connecticut, Colorado, Hawaii, Maine, Maryland, Massachusetts, New Jersey, New York, North Carolina, Oregon, Pennsylvania, Rhode Island, Vermont, Washington
County	All counties in above listed states
Vehicle Type	Medium-duty or Heavy-duty
Electrifiable (95th percentile of trucks that return to depot after fewer than 300 miles traveled)	True or False
Number of vehicles	Number of vehicles tracked by Geotab

Table VI.3.2 Geotab Telematics Data Schema: Annual and Daily

Variable Name	Value Type/Details
Daily: number of visits to depot	Average, standard devation 5th, 25th, 50th, 75th, 95th percentiles
Daily: duration of time spent at depot	
Daily: duration of time spent driving	
Daily: driving distance	
Daily: driving speed	
Daily: duration of time spent stopped away from depot	
Daily: count of all stops	
Annual: count of operational days	
Annual: count of non-operational days	

Table VI.3.3 Geotab Telematics Data Schema: Hourly

Variable Name	Value Type/Details
Hourly: Time stopped at depot	Average, standard devation 5th, 25th, 50th, 75th, 95th percentiles
Hourly: Time stopped away from depot	
Hourly: Time driving	

Energy and Infrastructure Requirements

We estimated required daily energy demand per truck by assuming that MD trucks consume, on average, 1.3 kilowatt-hours per mile and HD trucks consume 2.5 kilowatt-hours per mile (alternating current), consistent with the conservative estimate from California Air Resources Board [7]. In addition, we estimated needed charging infrastructure power in kW per truck under various scenarios, using daily energy demand and daily time spent at the depot (i.e., the potential window when the truck could be charging). Our base charging scenario assumes that a truck can charge at any time of day if it is stopped at the depot, and, for the sake of simplicity, we assume that each vehicle has a dedicated charger. We also considered an overnight charging scenario in which trucks can charge between the hours of 10PM-8AM while at the depot as the default scenario. Limiting the hours during which trucks can charge generally increases the required charger capacity in kW because the daily energy requirements in kWh remain unchanged, while the available charging window in hours decreases.

Load Curves (work ongoing)

We estimated 24-hour load curves at the county level using a Monte Carlo simulation to statistically determine the proportion of trucks at the depot during every hour of the day. We can also incorporate 'no charge times' depending on the charging scenario to approximate load curves under utility time-of-use rates. We adjusted the magnitude of the load to ensure that the total area under the curve is equal to the total daily energy required by the electric trucks.

Results

We analyzed telematics data for trucks in 15 states, encompassing 437 counties. Altogether, we identified 592,000 electrifiable MD trucks and 388,000 electrifiable HD trucks. These electrifiable trucks drive a combined total of 22 billion miles annually and would require about 41 TWh of energy per year, if electric, including charging losses.

Figure VI.3.1 shows overall truck populations for each of the 15 ACT states for medium-duty trucks (MDTs) and heavy-duty trucks (HDTs). The electrifiable populations are shown in green, while the remaining truck populations are shown in grey. California, New York, North Carolina, and Pennsylvania have large numbers of trucks that are not electrifiable based on our criteria. These are typically high mileage trucks, often HD, which drive long-haul routes, evident in Figure VI.3.2, which shows vehicle miles traveled (VMT). Figure VI.3.3(a) shows the proportion of vehicles by state that are electrifiable, and Figure VI.3.3(b) shows the VMT by state and the vehicle class, which is particularly helpful to understanding the potential electrification of trucks in states where the truck population is small. For example, while Hawaii has a very small truck population relative to other ACT states (refer to Figure VI.3.1), the proportion of trucks and truck miles that are electrifiable in Hawaii is higher than in any other state (refer to Figure VI.3.3) to due to Hawaii's island geography.

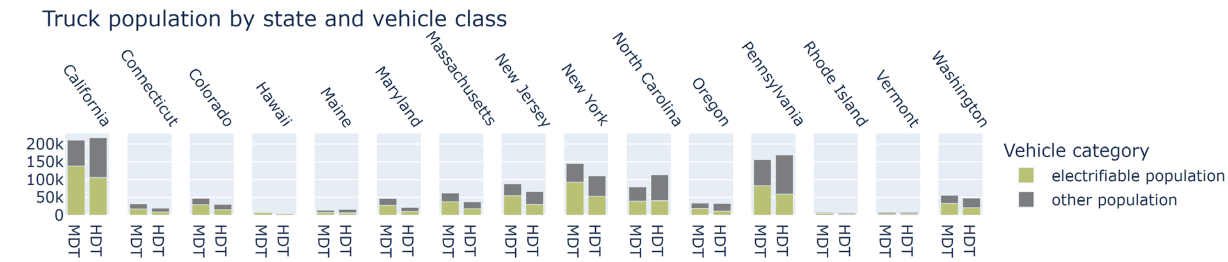


Figure VI.3.1 Truck population by state, vehicle class, and electrifiability. Source: Rocky Mountain Institute

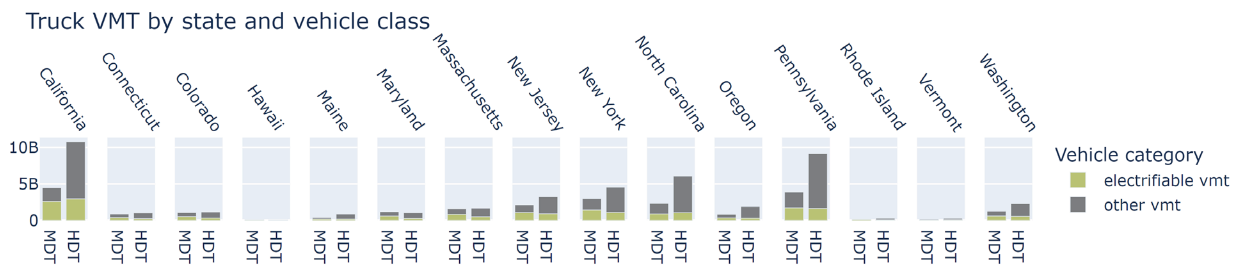
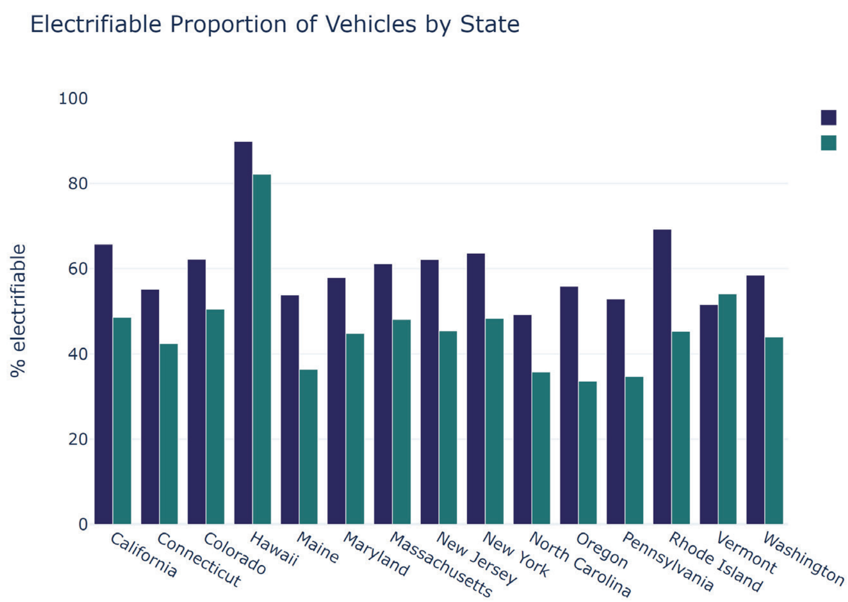
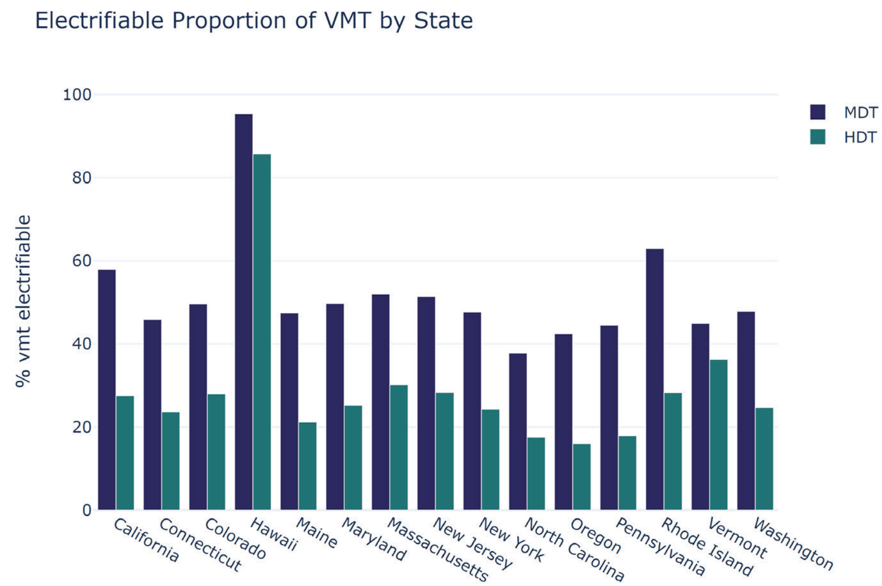


Figure VI.3.2 Truck VMT by state, vehicle class, and electrifiability. Source: Rocky Mountain Institute



(a)



(b)

Figure VI.3.3 (a) Electrifiable proportion of vehicles and (b) vehicle miles traveled by state and vehicle class. Source: Rocky Mountain Institute

We evaluate the required charging capacity in kW per vehicle using the aforementioned methodology, which uses the 75th percentile of daily mileage to calculate daily energy needs. We further considered two different charging scenarios: (1) charging is allowed anytime a truck is at the depot and (2) charging is allowed between the hours of 10PM and 8AM if a truck is at the depot. The resulting charging capacities from these scenarios are shown in Figure VI.3.4 and Figure VI.3.5, respectively. In the "anytime" charging scenario, charging capacity required per vehicle never exceeds 150 kW and is often under 60 kW. The limited charging window of the overnight scenario increases charging capacity needs, and we identified five counties in which per truck charging capacity exceeds 150 kW (points in the pink region in Figure VI.3.5). However, per truck charging capacity typically remains under 100 kW.

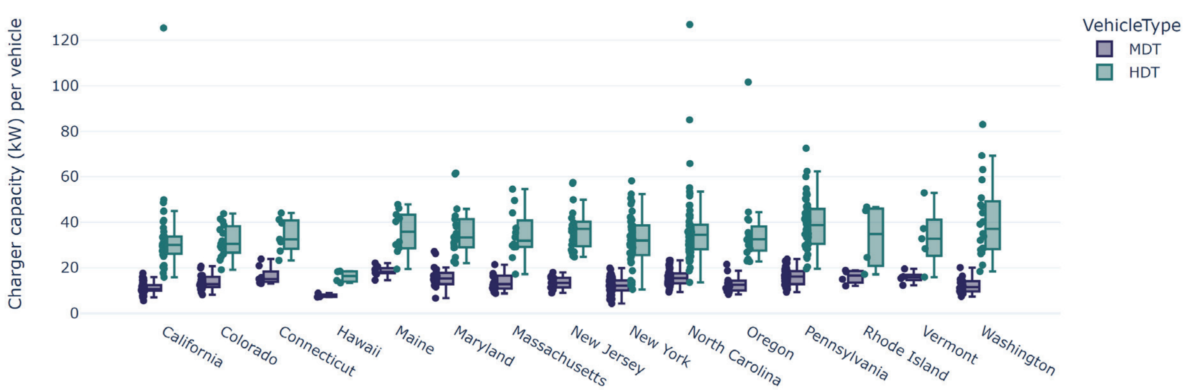


Figure VI.3.4 Charging capacity in kW required per truck in the anytime charging scenario. Box plots are shown as well as underlying distributions (each point represents a county). Source: Rocky Mountain Institute

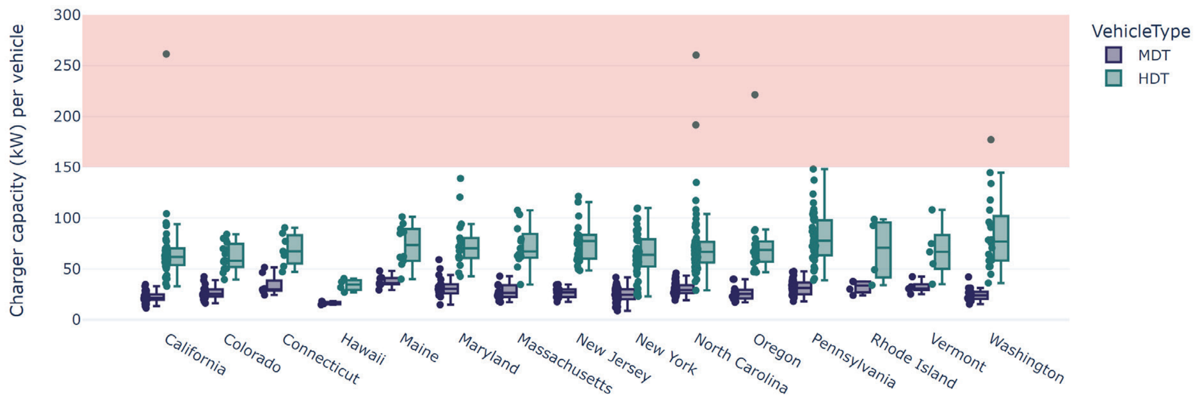


Figure VI.3.5 Charging capacity in kW required per truck in the **overnight** charging scenario. Box plots are shown as well as underlying distributions (each point represents a county). Source: Rocky Mountain Institute

Figure VI.3.6 and Figure VI.3.7 are examples of dashboard visuals that will eventually be available in a public-facing tool. Figure VI.3.6 shows a national overview of electrifiable trucks by county with brighter colors for counties with high numbers of electrifiable MDHD trucks and darker colors for counties with fewer electrifiable MDHD trucks. Uncolored counties in the states analyzed are due to Geotab privacy filters. Because too few trucks travel in these counties daily, it could be possible to identify the vehicle fleet and jeopardize its anonymity. We are working with Geotab to aggregate data at a regional geographic resolution so that we can show data in these areas.

Figure VI.3.7 shows an example of a deeper look at trucks by county in the state of Washington. An example use case of the dashboard is shown in which a policymaker can compare King County and Spokane County. Users will be able to compare counties initially on the following metrics: number and percent of electrifiable MDTs; number and percent of electrifiable HDTs; electrifiable VMT by vehicle class; and annual energy demand in GWh. Users will also be able to view a county-level aggregate load curve showing energy use as a function of time of day for different charging scenarios.

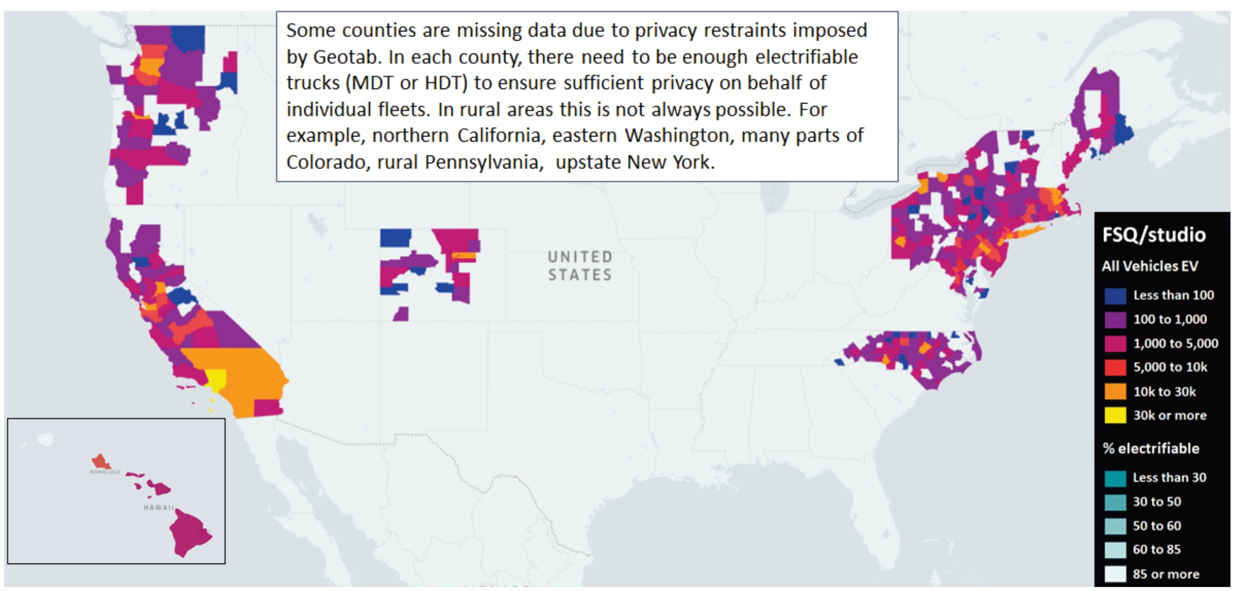


Figure VI.3.6 Dashboard visual: County-level view of electrifiable trucks (colored by truck population) in the 15 ACT states. Source: Rocky Mountain Institute

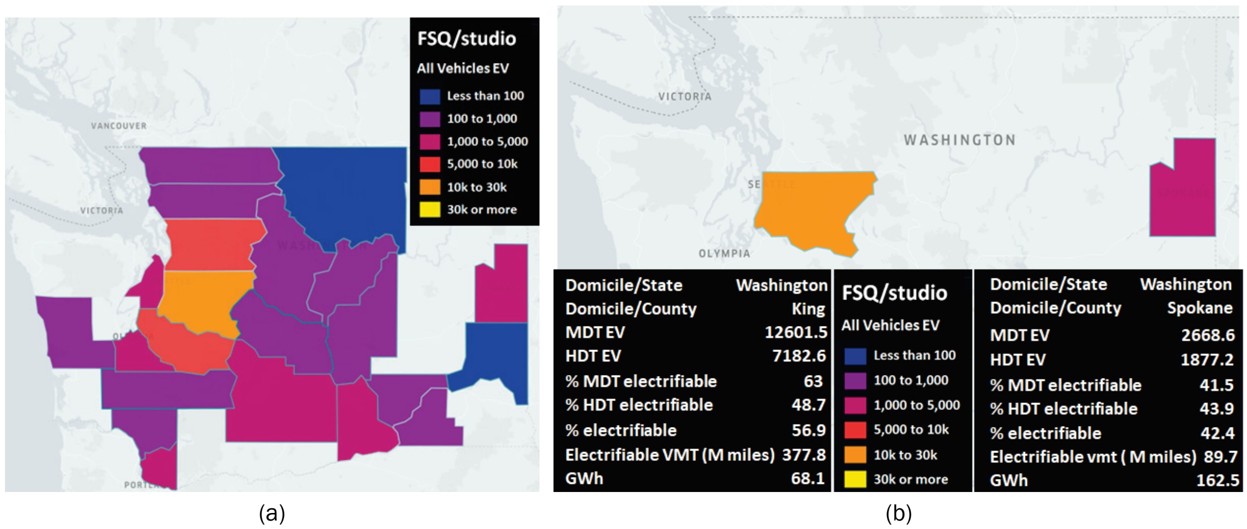


Figure VI.3.7 Dashboard visual: (a) County level view of electrifiable trucks (colored by truck population) in Washington with (b) a two-county highlight of King County and Spokane County. Source: Rocky Mountain Institute

Conclusions

Many trucks in the United States are electrifiable today based on their current duty cycles and available electric truck models. In aggregate, the annual electricity needed to power these trucks is 3-4% of the annual electricity consumption in the 15 states analyzed for this work. Our work indicates that depending on the time spent at depot (available for charging), electrifiable trucks may be able to use relatively low power infrastructure. To further investigate this, we are currently building load curves to understand both average and peak loads at a county level.

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