U.S. DEPARTMENT OF ENERGY

Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Analysis Program

2023 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, enabling important improvements in fuel economy and the efficiency of the transportation system.

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

Michelle Avillanoza
Operations Supervisor and
Analysis Program Manager
Analysis Program
Vehicles Technologies Office

Raphael Isaac
Technology Manager
Analysis Program
Vehicle Technologies Office

Patrick Walsh
Technology Manager
Analysis Program
Vehicle Technologies Office

Acronyms and Abbreviations

Symbols and Numbers

ABM	agent-based model
ACT	Advanced Clean Truck
ADOPT	Automotive Deployment Options Projection Tool
AEO	Annual Energy Outlook
ANL or Argonne	Argonne National Laboratory
ASTM	American Society for Testing and Materials
AWS	Amazon Web Services

B

B20	20% biodiesel blend
BatPaC	Battery Performance and Cost
BEV(s)	battery electric vehicle(s)
BILP	binary integer linear program
BP	budget period
BREVO	Battery Run-down under Electric Vehicle Operation (model name)
BTMS	battery thermal management system

C

C2G	cradle-to-grave
CBSA	core-based statistical area
CO_2	carbon dioxide
CO_2-eq	carbon dioxide equivalent
COVID-19	coronavirus disease of 2019
CV(s)	commercial vehicle(s)

D

DCFC	direct current fast charger (or charging)
DER	distributed energy resources
DGE	diesel gallon equivalent
DOE	U.S. Department of Energy
dsgrid	demand-side grid
dsgrid-flex	demand-side grid flexibility

E

e-axle	electric (vehicle) axle
e-bike	electric bike
e-drive	electronic drive
EERE	Energy Efficiency and Renewable Energy
e.g.	for example
EIA	U.S. Energy Information Administration
eMDHD	electric medium-duty/heavy-duty (vehicle)
EMF	Energy Modeling Forum
EOL	end-of-life
EOLR	end-of-life recycling
EPA	U.S. Environmental Protection Agency
EPRI	Electric Power Research Institute
EV(s)	electric vehicle(s)
EVI-Pro	Electric Vehicle Infrastructure Projection tool
EVI-X	Electric Vehicle Infrastructure suite for X number of electric vehicle charging infrastructure analysis tools
EVMC	electric vehicle managed charging
eVMT	electric vehicle miles traveled Infrastructure
EVSE	electric vehicle supply equipment

F

FCEV(s)	fuel cell electric vehicle(s)
FCFS	first-come-first-served
FOTW	fact of the week
FY	fiscal year

G

g	grams (when referring to mass)
GDP	gross domestic product
GHG	greenhouse gases
GREET®	Greenhouse gases, Regulated Emissions, and Energy use in Transportation
GTL FTD	gas-to-liquid Fischer–Tropsch diesel
GWh	gigawatt hour

H

H_2	hydrogen
H2@Scale	a U.S. Department of Energy initiative that brings together stakeholders to advance affordable hydrogen production, transport, storage, and utilization to enable decarbonization and revenue opportunities across multiple sectors
HD	heavy duty
HDT	heavy-duty truck
HDV	heavy-duty vehicle
HERE	a consumer mapping application that works on smartphones or through a web browser formerly Nokia Maps and HERE Maps
HEV(s)	hybrid electric vehicle(s)
HEVII	Heavy-Duty Electric Vehicle Integration and Implementation
HEVI-LOAD	Heavy-Duty Electric Vehicle Infrastructure – Load Operations and Deployment

I

I-45	Interstate 45
ICE/ICEV	internal combustion engine/vehicle
i.e.	that is
IMPLAN	a model utilizing an economic modeling technique called Input-Output analysis and a Social Accounting Matrix, which is a type of applied economic analysis that tracks the interdependence among various producing and consuming industries of an economy and the spending of households
INRIX	A provider of traffic information
IRA	Inflation Reduction Act
ISATT	Integrated Systems Analysis Technical Team

K

kg	kilogram
kW	kilowatt
kWh	kilowatt hour

L

lb. or lbs.	pound or pounds
LCA	life cycle analysis
LCI	life cycle inventory
LD(V(s))	light duty (vehicle (s))
Li	lithium
LiB	lithium-ion battery

LMP	locational marginal price

M

MA3T	Market Acceptance of Advanced Automotive Technologies
MATLAB	MATrix LABoratory, a multi-paradigm numerical computing environment and programming language
MCP	mobility carbon productivity
MD	medium duty
MDHD/MDHDV or MHDV	medium- and heavy-duty vehicle
MDT	medium-duty truck
MHDV(s)	medium- and heavy-duty vehicle(s)
MMTCe	million metric tons of carbon equivalent
MOVES	Motor Vehicle Emission Simulator
MRO	Midwest Reliability Organization
MS	Microsoft
MSA	metropolitan statistical areas
MW	megawatt
MWh	megawatt hour(s)

N

NEAT	Non-Light Duty Energy and Greenhouse Gs Emissions Accounting Tool
NEVI	National Electric Vehicle Infrastructure
NG	natural gas
NREL	National Renewable Energy Laboratory

O

OEM	original equipment manufacturer
OMEGA	Optimization Model for reducing Emissions of Greenhouse Gases from Automobiles
OR-AGENT	Optimal Regional Architecture Generation for Electrified National Transport
ORNL	Oak Ridge National Laboratory
OR-SAGE	Oak Ridge Siting Analysis for Power Generation Expansion
OSU	Ohio State University

P

PCO	perceived cost of ownership
PDF	portable document format

PEV(s)	plug-in electric vehicle(s)
PHEV(s)	plug-in hybrid electric vehicle(s)
PJM	a regional transmission organization that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia.
PV	photovoltaic

R

RC	recycled content
RD100	100% renewable diesel
R&D	research and development
ReEDS	Regional Energy Deployment System
reV	Renewable Energy Potential (NREL siting tool)
RIMS	Regional Input-Output Modeling System

S

SAE	Society of Automotive Engineers
SCOOT	Screening for City Opportunities Online Tool
SMART	Systems and Modeling for Accelerated Research in Transportation
SMR	steam-methane reforming
SP/RP	stated preference/revealed preference
ST	short term
SUV	sport utility vehicle

T

TAC	technical advisory committee
TCO	total cost of ownership
TDM	travel demand management
TDP	Transportation Data Program
TechScape	technology landscape
TEEM	Transportation Energy Evolution Modeling
TEMPO	Transportation Energy & Mobility Pathway Options
TNC(s)	transportation network company(ies)
TTW	tank-to-wheel
TWh	terawatt-hour

U

u	utility (a factor in a probability calculation)
UIUC	University of Illinois Urbana-Champaign
U.S.	United States
U.S. DRIVE	Driving Research and Innovation for Vehicle Efficiency and Energy Sustainability
UVM	Used Vehicle Model

V

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	Vehicles Technology Office

W

Wh	watt hour
Wh/kg	watt hours per kilogram
WTT	well-to-tank
WTW	wheel-to-wheel

Z

ZEV(s)	zero emission vehicle(s)

Executive Summary

During fiscal year 2023 (FY 2023), the U.S. Department of Energy Vehicle Technologies Office (VTO) funded analysis projects supportive of VTO's goals to pursue research relevant to (i) decarbonization of transportation fuels and related infrastructure across modes and (ii) transportation mobility technologies that enable a reduction in system vehicle miles traveled (VMT). Topics included electric vehicles for passenger and freight applications, mobility system technologies and trends, impacts of electric vehicles on the grid, and other topics, with an emphasis on new, efficient, and clean motility options that are affordable for all Americans and that promote sustainable economic growth, equity, and increased energy security.

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 2023. Each of the progress reports includes project objectives, approach, and highlights of the technical results that were accomplished during FY 2023.

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Vehicle Technologies Office Overview

Vehicles move our national economy. Each year in the United States, 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 27% 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 in decarbonizing the transportation sector and address the climate crisis by driving innovation and deploying clean transportation technologies, all while maintaining transportation service quality and safety.

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 (including automated and connected vehicles as well as innovations in efficiency-enhancing connected infrastructure); innovative powertrains to reduce greenhouse gas (GHG) and criteria emissions from hard to decarbonize off-road, maritime, rail, and aviation sectors; and technology integration that helps demonstrate and deploy new technology at the community level. Across these technology areas and in partnership with industry, VTO has established aggressive technology targets to focus RDD&D efforts and ensure there are pathways for technology transfer of federally supported innovations into commercial applications.

VTO is uniquely positioned to accelerate sustainable transportation technologies due to strategic public–private research partnerships with industry (e.g., U.S. DRIVE, 21st Century Truck Partnership) that leverage relevant expertise. These partnerships prevent duplication of effort, focus DOE research on critical RDD&D barriers, and accelerate progress. Working closely and in collaboration with the Office of Energy Efficiency and Renewable Energy's Bioenergy Technologies and Hydrogen and Fuel Cell Technologies Offices, 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 Off-Road, Rail, Marine, and Aviation; Energy Efficient Mobility Systems; Technology Integration; and Analysis. Each year, VTO's technology areas prepare an Annual Progress Report (APR) that details progress and accomplishments during the fiscal year. VTO is pleased to submit this APR for Fiscal Year (FY) 2023. The APR presents descriptions of each active project in FY 2023, including funding, objectives, approach, results, and conclusions.

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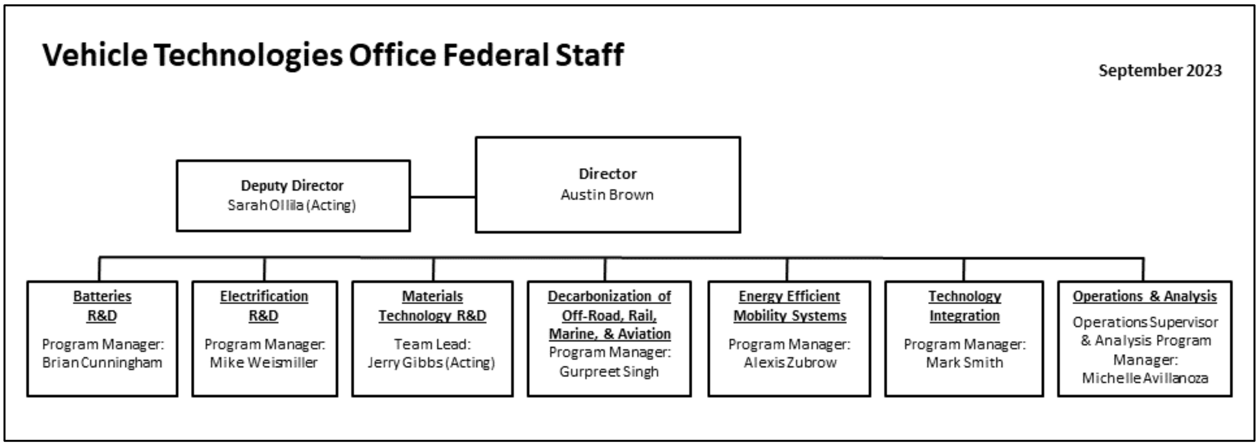
[1] Bureau of Transportation Statistics, DOT, Transportation Statistics Annual Report 2020, Table 4-1, https://www.bts.gov/tsar.
[2] Davis, Stacy C, and Robert G Boundy. Transportation Energy Data Book: Edition 40. Oak Ridge, TN: Oak Ridge National Laboratory 2022. https://doi.org/10.2172/1878695. . Table 3.09 Shares of Highway Vehicle-Miles Traveled by Vehicle Type, 1970-2019.
[3] Ibid. Table 2.02 U.S. Consumption of Total Energy by End-use Sector, 1950-2021.
[4] Ibid. Table 11.1 Average Annual Expenditures of Households by Income, 2020.
[5] Ibid. Table 2.03 Distribution of Energy Consumption by Source and Sector, 1973 and 2021.
[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). VTO funds research, development, demonstration, and deployment of new, efficient, and clean mobility options that are affordable for all Americans and that promote sustainable economic growth, equity, and increased energy security.

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.

Program Organization Matrix

As indicated above, the Analysis Program activities are organized within three areas: (1) Data, (2) Modeling and Simulation, and (3) Applied Analysis. The below graphic demonstrates the characteristics of each of these program areas:

Data	• Create and maintain a strong foundation of reliable, up-to-date, and easily accessible data • Provide insight into transportation and energy use for a broad range of internal and external stakeholders
Modeling & Simulation	• Build and maintain relevant analytical models supportive of techno-economic analysis • Quantify outcomes in terms of GHG emissions, technology implementation cost, equity and affordability, efficiency, and resiliency
Applied Analysis	• Provide insights into critical transportation energy problems through integrated analyses • Provide inputs and metrics for program planning, budget justification, and program evaluation

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

Which vehicle use domains—including vehicle design, powertrain technologies, increased automation and system connectivity, greater penetration of shared vehicles and micromobility, and a better understanding of travel patterns—offer the potential to provide clean mobility benefits and at a reasonable cost to both businesses and the consumer? In which applications can specific new technologies make the greatest impact?

- What trends in VMT, vehicle ownership, fuel and technology choice, infrastructure development, consumer behavior, and other factors are likely to impact the achievement of future benefits?
- As sales of electric vehicles (EVs) grow, how will charging infrastructure needs evolve? How will use of these vehicles impact the electricity grid, and vice versa? How can this infrastructure be made available to consumers across the socioeconomic spectrum, and how might the infrastructure best address the needs of individuals living in a variety of different housing/neighborhood types?
- As demand for freight transportation grows, how can we improve the efficiency of moving the goods we buy? How can a variety of medium- and heavy-duty vehicle technologies—including advanced lightweight materials, advanced engine designs, and electric powertrain technologies—and modes help the nation to achieve key energy and environmental goals despite this demand growth?
- How will developments in vehicle connectivity and autonomy impact energy demand? How do we ensure that these developments lead to a safe, efficient, and clean transportation system?

What will the future look like if we meet all of our subprogram targets? What if our subprograms fall short?

Goals

The goals of the VTO Analysis Program are to:

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

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

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

I Technology and Market Data

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

Stacy C. Davis, Principal Investigator
Oak Ridge National Laboratory
2360 Cherahala Blvd.
Knoxville, TN 37932
E-mail: DavisSC@ornl.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Patrick Walsh, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Patrick.Walsh@ee.doe.gov

Start Date: October 1, 2022	End Date: September 30, 2025	
Project Funding (FY23): $535,000	DOE share: $535,000	Non-DOE share: $0
Project Funding (FY24–FY25): $960,000	DOE share: $960,000	Non-DOE share: $0
Total Expected Project Funding: $1,495,000	DOE share: $1,495,000	Non-DOE share: $0

Project Introduction

The Transportation Energy Data Book (TEDB) and Vehicle Technologies Fact of the Week (FOTW) are created by Oak Ridge National Laboratory's (ORNL's) 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) 2023, the project (1) produced the text, graphics, and data for a FOTW every week, (2) created programs to automate the back-end data collection of the Transportation Energy Data Book, an online publication that is typically published once a year and updated periodically throughout the year, and (3) worked on 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 [NREL]), government agencies (e.g., the Federal Highway Administration of the U.S. 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 Transportation Energy Data Book, including PDF and MS Excel files, is posted on a website hosted by ORNL (https://tedb.ornl.gov/). The major topics for the TDP publications are provided in Table I.1.1.

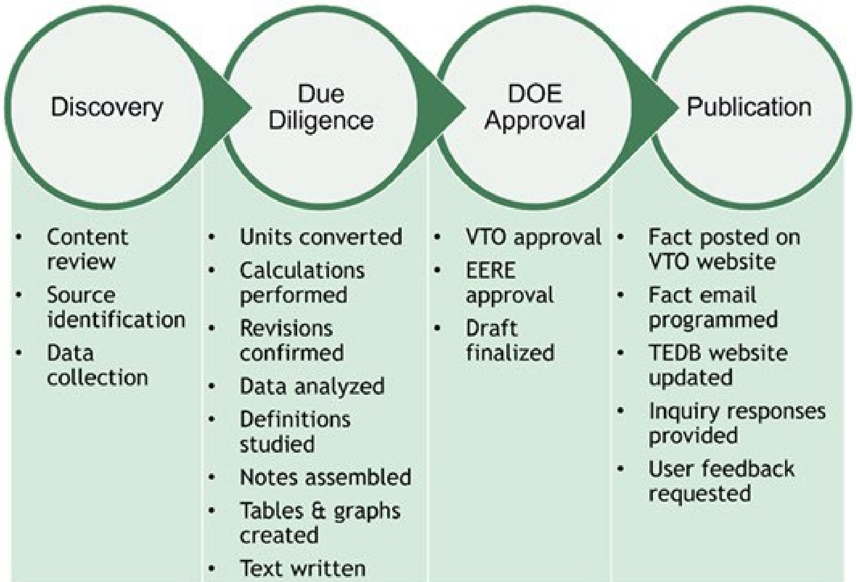


Figure I.1.1 Approach for the transportation data program at ORNL. Source: ORNL

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 and Characteristics	Fuel Economy
Heavy Vehicles and Characteristics	Travel Behavior
Alternative Fuel and Advanced Technology Vehicles and Characteristics	Gasoline
Transit and Other Shared Mobility	Electric Vehicles
Fleet Vehicles and Characteristics	Cost to Consumer
Household Vehicles and Characteristics	Diesel
Nonhighway Modes	Import/Export
Transportation and the Economy	Infrastructure
Emissions	Heavy-Duty Vehicles
Energy Conversions	Behavior/Ownership
	And More...

Results

The weekly email for the FOTW began on July 27, 2015, with 50 email subscribers. As of the end of FY 2023, there were 23,245 subscribers to the newsletter.

FOTW 1258 through 1309, shown in Table I.1.2, were posted on the VTO website during FY 2023. For FY 2023, FOTW content accounted for 592,926 pageviews, or 28% of all VTO website pageviews. Of the FOTW pageviews, 329,578 were unique visits, meaning that some visitors (263,348) to FOTW content were repeat visitors. Of all VTO website visits, 32% (335,774) entered the VTO website through a FOTW landing page. Fact 915, Average Historical Annual Gasoline Pump Price from 1929–2015, had the second-highest number of pageviews of any VTO website page—190,533, or 16% of all website pageviews during the fiscal year. Another FOTW on gasoline prices was the third-highest, with 100,750 pageviews (11%).

Table I.1.2 Major Topics for the Transportation Data Program at Oak Ridge National Laboratory

Date Posted	Fact Title
September 25, 2023	There Were Four Counties in California with Electric Vehicle (EV) Market Penetration Exceeding 30%
September 18, 2023	67% of All Housing Units Have Vehicle Parking Within 20 Feet of an Electrical Outlet
September 11, 2023	EV Charging Consumed Less Energy than Water Heating in a Typical U.S. Household
September 4, 2023	Model Year 2022 Light-Duty Vehicles Sold in the U.S. Averaged 26.4 Miles Per Gallon
August 28, 2023	Growth in Vehicles Outpaced Growth in Population and Licensed Drivers from 1960 to 2021
August 21, 2023	In 2023, Non-Fossil Fuel Sources Were 86% of New Electric Utility Generation Capacity
August 14, 2023	From Cradle to Grave, EVs Have Fewer GHG Emissions Than Conventional Vehicles
August 7, 2023	In 2021, 87% of U.S. Truck Freight Tonnage Was Shipped Less than 250 Miles
July 31, 2023	Two-Thirds of Freight Tonnage and Three-Fourths of Freight Value in the U.S. Was Moved by Truck in 2021
July 24, 2023	In the First Quarter of 2023, 21.5% of all Public EV Charge Ports Were for DC Fast Charging
July 17, 2023	EV Charging Ports in the U.S. Nearly Doubled in the Past Three Years
July 10, 2023	Highest EPA-Rated Fuel Economy for Model Year 2023 Was 140 MPGe, Achieved by 2 EV Models
July 3, 2023	For the Past Six Months, Average Nationwide Monthly Gas Prices Were Below $4/Gallon
July 26, 2023	Data from the Six Largest Bikeshare Systems Show that Trips Are on the Rise
June 19, 2023	All-Electric Cars Offer Wide Selection of Ranges
June 12, 2023	In 2021, Combination Trucks Were Driven More Than 62,000 Miles Annually on Average
June 5, 2023	More Heavy Trucks Operated at 34,000–36,000 Pounds than Any Other Weight Category
May 29, 2023	Light Trucks Dominated Sales of Light-Duty Vehicles with an MSRP over $30,000
May 22, 2023	Net Generation of Electricity from Renewable Sources Exceeded Coal and Nuclear in 2022
May 15, 2023	In Model Year 2022, the Longest-Range EV Reached 520 Miles on a Single Charge
May 8, 2023	New Vehicle Fuel Economy Improved by 33% 1980–2022 While Performance Increased
May 1, 2023	U.S. Motor Fuel Taxes are Lower Than in Other Developed Countries

Date Posted	Fact Title
April 24, 2023	Wyoming has the Highest Per Capita Number of Registered Light-Duty Vehicles
April 17, 2023	Top 10 New EV Registrations in 2022 Were Models with Long Ranges
April 10, 2023	Vehicle Miles Traveled in 2021 and 2022 Followed a Monthly Pattern Similar to Those Preceding the Pandemic
April 4, 2023	Average Travel Time to Work Was About 27 Minutes in 2021
March 27, 2023	The Share of At-Home Workers Doubled From 2018 to 2021
March 20, 2023	The Number of Light-Duty All-EV Models Nearly Doubled from Model Year 2021 to 2022
March 13, 2023	Over 14% of Light Vehicles Produced in 2022 had a Fuel Economy of 35 mpg or Higher
March 6, 2023	More than 99% of All Light-Duty Vehicles Produced in 2022 Had Automatic Transmissions
February 27, 2023	Seven States and DC Had More Than 10 Plug-In Vehicle Registrations per 1,000 People
February 20, 2023	Most Battery Cells and Packs in Plug-in Electric Vehicles (PEVs) Sold From 2010 to 2021 Were Domestically Produced
February 13, 2023	Nearly 60% of Light-Duty Vehicles Produced in 2022 had All-Wheel or Four-Wheel Drive
February 6, 2023	U.S. New Light-Duty Vehicle Sales Totaled 13.8 Million in 2022
January 30, 2023	Monthly PEV Sales Exceeded 7% of New Light Vehicle Sales for the First Time in September 2022
January 23, 2023	20% of Electricity in the U.S. Was Generated from Renewable Sources
January 16, 2023	FuelEconomy.gov Releases Top Ten Lists for Model Year 2023
January 9, 2023	EV Battery Pack Costs in 2022 Are Nearly 90% Lower Than in 2008
January 2, 2023	EV Battery Production Capacity in 2030 is Projected to be 20 Times Greater than 2021
December 26, 2022	Premium Gasoline Refiner Sales Have Grown More Than 30% Since 2008
December 19, 2022	Average Annual Price Difference Between Regular and Premium Gas was 68 Cents/Gallon, 2021
December 12, 2022	As of 2021, Two-Thirds of U.S. Housing Units Had a Garage or Carport
December 5, 2022	Plug-In EVs Reduced CO_2 Emissions by 5.5 Million Metric Tons in 2021
November 28, 2022	Light-Duty PEVs in the United States Traveled 19 Billion Miles on Electricity in 2021
November 21, 2022	In 2021, over 70% of All Plug-In Vehicles in the U.S. Were Assembled in North America
November 14, 2022	Fuel Economy Improvements in Low-Miles-Per-Gallon (MPG) Vehicles have Greatest Impact Reducing CO_2
November 7, 2022	Fuel Economy Improvements in Low-MPG Vehicles Yield the Greatest Savings
October 31, 2022	The United States Has Designated 75,820 Miles of EV Charging Corridors as of July 2022
October 24, 2022	Truck Travel Between States Was Highest from New York to New Jersey
October 17, 2022	Chicago Census Tracts with High-Income Households Used Ride Hailing More Often
October 10, 2022	Transportation Sector Responsible for 50% of Energy-Related CO_2 Emissions for 11 States
October 3, 2022	40% of the Electricity Produced in U.S. Was Derived from Non-Fossil Fuel Sources

This year, significant work was performed on back-end data collection for the Transportation Energy Data Book. ORNL utilized application programming interfaces (APIs) from various data sources to efficiently acquire, process, and merge relevant datasets and explored multiple output formats—including LaTeX, Excel (.xlsx), and CSV (comma-separated values) files—to determine the most effective method for data representation. It was determined that a singular, up-to-date Excel file that serves as a central source for future table updates was needed to enhance the consistency and accuracy of the data. A comprehensive Excel file was established as the optimal approach for combining data from automated acquisitions, and an automated process was developed to streamline data updates from the latest specified sources, generating an updated file.

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 formats. In addition to enabling data access, the website has five rotating data highlights (changed several times a year), 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. 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 42,800 pageviews in FY 2023. Google Scholar reports a total of about 4,250 citations for the Transportation Energy Data Book.

Data collected in the TDP have also provided input to other VTO programs and other agency models, such as ORNL's Market Acceptance of Advanced Automotive Technologies (MA3T) model, Argonne National Laboratory'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.

In November 2022, the DOE Clean Cities Program asked ORNL to create a poster about the Transportation Energy Data Book for the 2022 Clean Cities Training Workshop in Lakeland, Colorado.

As part of the TDP, NREL began a medium/heavy truck data analysis in FY 2023 that will be completed in FY2024. A literature review and data availability assessment were completed.

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. ORNL. "Transportation Energy Data Book." Poster for the Clean Cities Training Workshop. November 2022.

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)

Yan Zhou, Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Lemont, IL 60565
E-mail: YZhou@anl.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: October 1, 2022 End Date: September 30, 2025
Project Funding: $250,000 DOE share: $250,000 Non-DOE share: $0

Project Introduction

The U.S. 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 (EVs) 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 EV use can offset petroleum consumption associated with conventional internal combustion engine vehicles, affecting oil prices and resource extraction.

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

Objectives

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

- **Electric drive vehicle sales tracking:** Collect monthly plug-in electric vehicle (PEV), hybrid electric vehicles, 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.
- **EV 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 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, in FY23. 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 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 options, 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 recent data availability of shared mobility (TNC, bikeshare, scooter share) and ownership mobility (personal bikes and e-bikes) technologies. Based on the data collected, this task assessed general usage and/or adoption trends by mobility type and analyzed usage characteristics across different mobility technologies and urban profiles. This task also summarized the energy and emissions impacts of micromobility technologies and synthesized the findings to date of micromobility impacts, anticipating future directions for research.

Results

Through December 2022, over 3.2 million PEVs had been sold in the United States, with 2.3 million of these BEVs and 996,000 PHEVs that can use gasoline. The PEV market is predominantly BEVs (around 80%) as of 2023. Cars used to be the most common EV category, but recently, sport utility vehicles/vans have overtaken cars as the lead category. Currently, there are almost no PHEV cars. This research team estimates that EVs have driven 95.7 billion miles on electricity since 2010, reducing gasoline consumption by 3.5 billion gallons cumulatively through 2022. In 2022, PEVs used 9 TWh of electricity to drive 28 billion miles, offsetting 690 million gallons of gasoline. The sales-weighted average BEV range reached 295 miles in 2022, before dropping slightly in 2023. The sales-weighted average BEV efficiency reached 300 Wh/mile, while overall PEV average efficiency was 335 Wh/mile (sales-weighted) in 2022. The 3.2 million PEVs in the United States combined to reduce consumer fuel costs by $2.5 billion (or almost $800 per vehicle relative to a comparable vehicle).

In 2022, higher gasoline prices led to savings of 9 cents per mile for BEVs and 5 cents per mile for PHEVs. Since 2010, 69% of PEVs sold in the United States have been assembled domestically, and over 180 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 from 2011 to 2022. California is the state with the most registered EVs, both in total number (Figure I.2.1) and in percentage share of all vehicles (Figure I.2.2).

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
2022	931	28	935	9000	7.0
Total	**3,281**	**95.7**	**3474**	**31260**	**26.08**

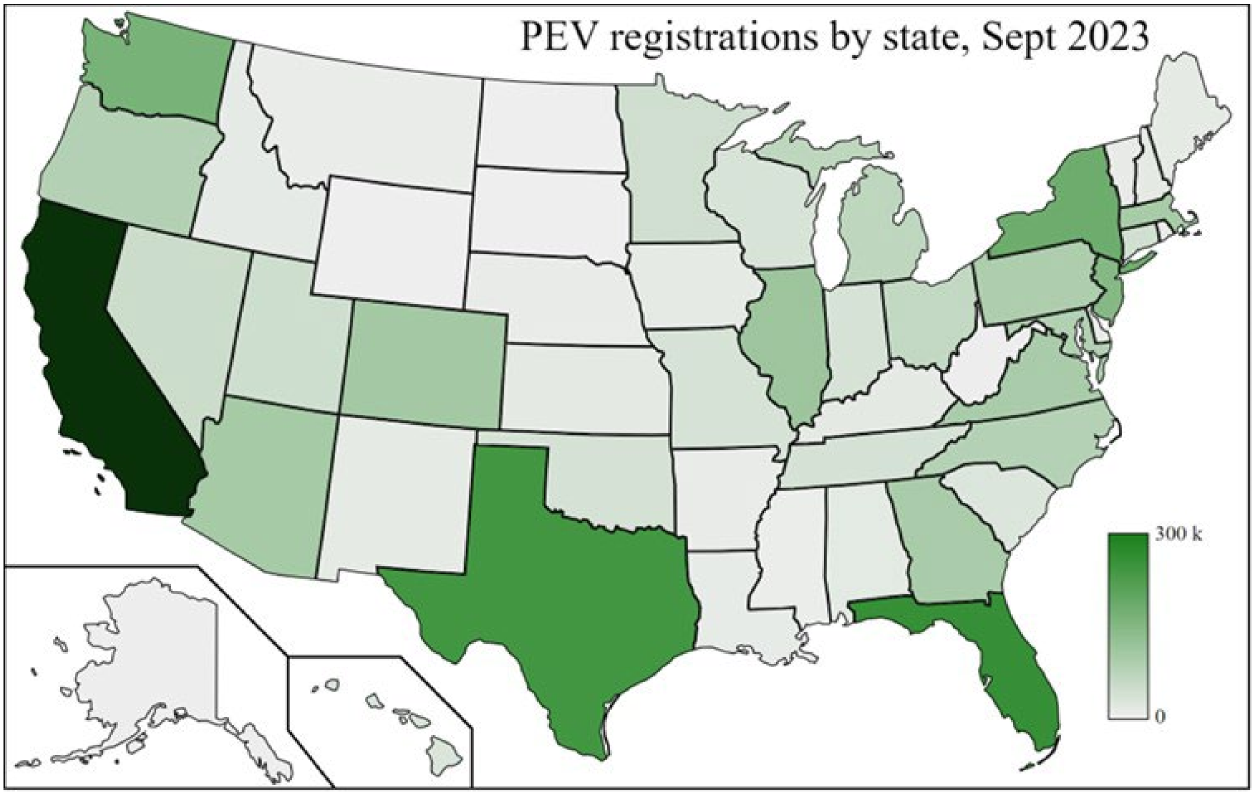


Figure I.2.1 PEV registration by state, September 2023. Source: Argonne

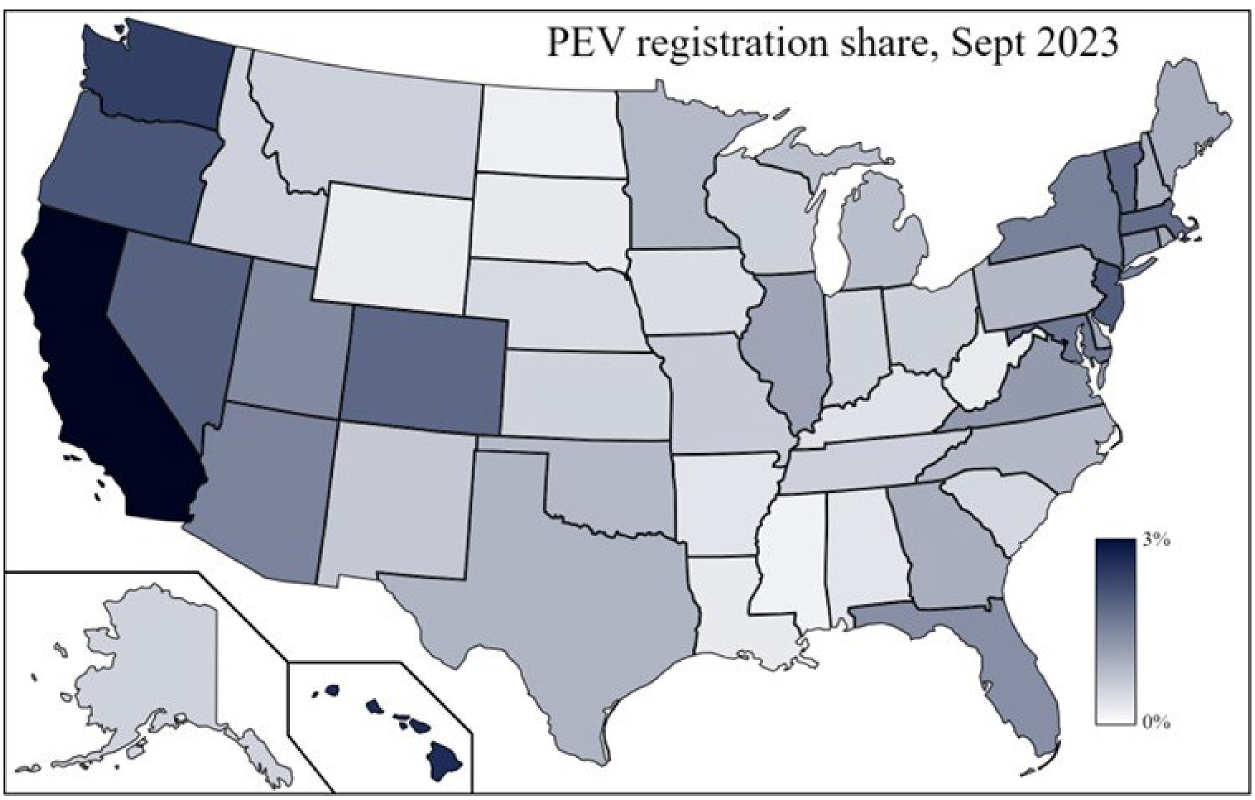


Figure I.2.2 PEV registration share by state, September 2023. Source: Argonne

Announcements of private-sector investments in U.S.-manufactured battery technologies have been increasing over the last few years, with 208 as of September 2023. There have also been 27 federal investment announcements. Figure I.2.3 shows locations of new announcements of minerals extraction and processing, battery component manufacturing, battery cell manufacturing, and battery pack manufacturing [1]. This includes formally announced mines for lithium, cobalt, and other battery minerals; processing facilities for battery minerals; facilities to produce battery components; and commercial and pilot-scale battery cell and pack manufacturing. It has been anticipated that the more than $100 billion in investments (private and federal) will create over 75,000 jobs [2].

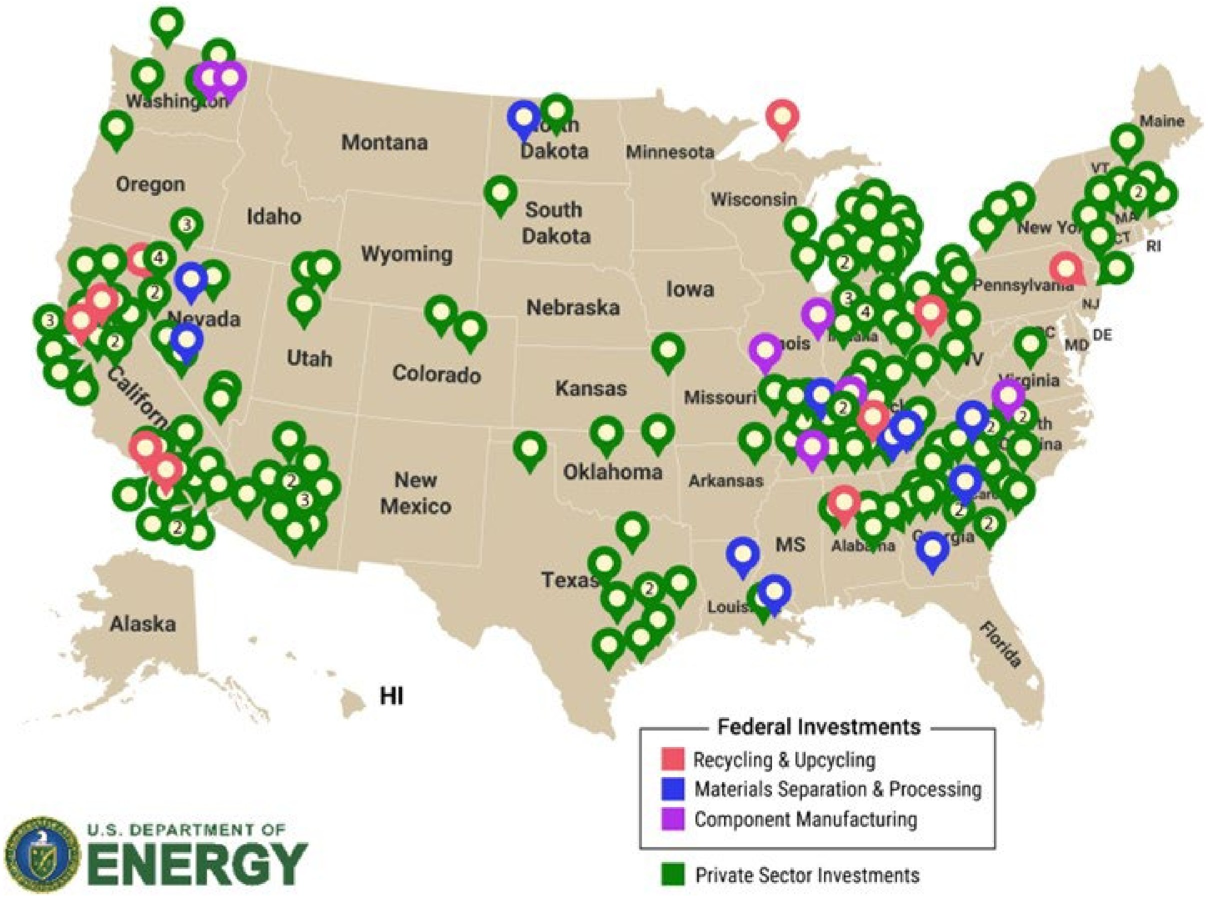


Figure I.2.3 Announced U.S.-manufactured battery investments as of September 2023 [1]

Conclusions

Between 2010 and 2022, over 3.2 million PEVs have been sold in the United States. These vehicles have been driven nearly 95.7 billion miles, displacing more than 3.5 billion gallons of gasoline, preventing about 26 million metric tons of greenhouse gases, and consuming 31 TWh of electricity nationally.

Most of the PEVs on the road were assembled in the United States, 40% of the total content is domestically sourced, and many of the battery packs and cells were built domestically as well. Over 180 GWh of battery capacity has been installed in PEVs since 2010. 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. More than $100 billion in investments (private and federal) in EV and the EV supply chain were announced between January 2021 and September 2023, and these investments will create over 75,000 jobs.

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.

References

1. "The Private Sector Accounts for 89% of Announced American-Made Battery Investment." VTO website. Fact of the Week #1315. November 6, 2023. https://www.energy.gov/eere/vehicles/articles/fotw-1315-november-6-2023-private-sector-accounts-89-announced-american-made.

2. "Building America's Clean Energy Future", DOE website, https://www.energy.gov/invest, accessed 12/31/2023.

Acknowledgments

This activity was supported by DOE VTO. The authors would like to thank Raphael Isaac, Noel Crisostomo, and Jacob Ward for their guidance and feedback. This work was supported in part by the DOE Office of Science and its Office of Workforce Development for Teachers and Scientists under the Science Undergraduate Laboratory Internships Program.

II Vehicle Modeling and Simulation

II.1 Analysis of Electric Heavy-Duty Driving and Infrastructure Requirements Within a Regional Area (Electric Power Research Institute)

Marcus Alexander, Principal Investigator
Electric Power Research Institute
3420 Hillview Ave
Palo Alto, CA 94304
E-mail: malexander@epri.com

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: October 1, 2020 End Date: September 30, 2024
Project Funding (FY23): $59,842 DOE share: $55,395 Non-DOE share: $4,447

Project Introduction

This project will analyze heavy-duty freight movement and will estimate the transmission and distribution impacts of electrification of heavy-duty freight vehicles. Currently Class 7 and 8 electric tractor trucks are available in early production form, 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 the potential difficulty and cost of installing infrastructure to recharge these vehicles, which may require "slow" charging (up to 20–100 kW per plug) to charge overnight 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 require 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 to utilities to society overall. The project will accomplish this goal by leveraging cutting-edge electrification and grid analytics to demonstrate new techniques to characterize electrification needs, align the needs with existing grid capacity, assess various electrification solution options where capacity is not available, and optimize for least-cost and reliability. This project will identify dominant cost factors and sensitivities associated with the electrical system reinforcement costs needed to serve these demands. Understanding these factors 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 task in this budget period is Task 6, Results Dissemination, which consists of two subtasks: (1) organizing a technology transfer workshop and (2) preparing the final report. The objective for Subtask 6.1 is to organize a workshop that targeted key stakeholders, providing an overview of the project process and presenting key findings. This workshop was intended to take place either online or at an appropriate Electric Power Research Institute (EPRI) conference.

The objective of Subtask 6.2 is to create a final report on the impacts of freight electrification within a region. The report will document the methodology, results, and key findings, along with general characteristics for each site, descriptions of the identified system expansion needs, and study assumptions. Additionally, the report will highlight key considerations and future needs to realize optimal least-cost integration solutions to support electrification of this component of the transportation sector.

Approach

Task 6.1: Organize Technology Transfer Workshop

Organizing the workshop consists of identifying the appropriate audience, scheduling the meeting, and presenting the results of this work.

Task 6.2: Write Project Report

Drafting the final report consists of outlining the report, collecting sections from each project participant, and writing a cohesive narrative.

Results

Task 6.1: Organize Technology Transfer Workshop

The workshop was successfully held at the EPRI Bus and Truck Working Council meeting on October 24, 2023.

Task 6.2: Write Project Report

The report writing was initiated in Fiscal Year (FY) 2023 but is continuing into FY 2024. Below is an excerpt that shows a summary of one part of the modeling.

Hosting Capacity Analysis

Prior to analyzing the integration of electric vehicles (EVs), it is insightful to understand the system's current capability. A hosting capacity analysis will investigate the amount of new load that each node can accommodate across a distribution feeder without experiencing undesirable system conditions. Based on the feeder model, the analysis will determine how much additional demand could be hosted at each location across the feeder, considering the very specific characteristics and topology of the feeder. A heatmap of the results from the analysis onto the feeder shown in Figure II.1.1 can help distribution planners to visualize the capability of the system to host additional load. Note that location (1) on the feeder has a hosting capacity of ~5.5 MW, location (2) has a capacity of ~3 MW, and location (3) has less than 1 MW of available capacity. These differences demonstrate that the available capacity on a distribution feeder to host new demand will vary not only from one feeder to another but also from one location to another within a feeder. The results also show that the analysis considers the feeder's specific characteristics when assessing the capability on the feeder.

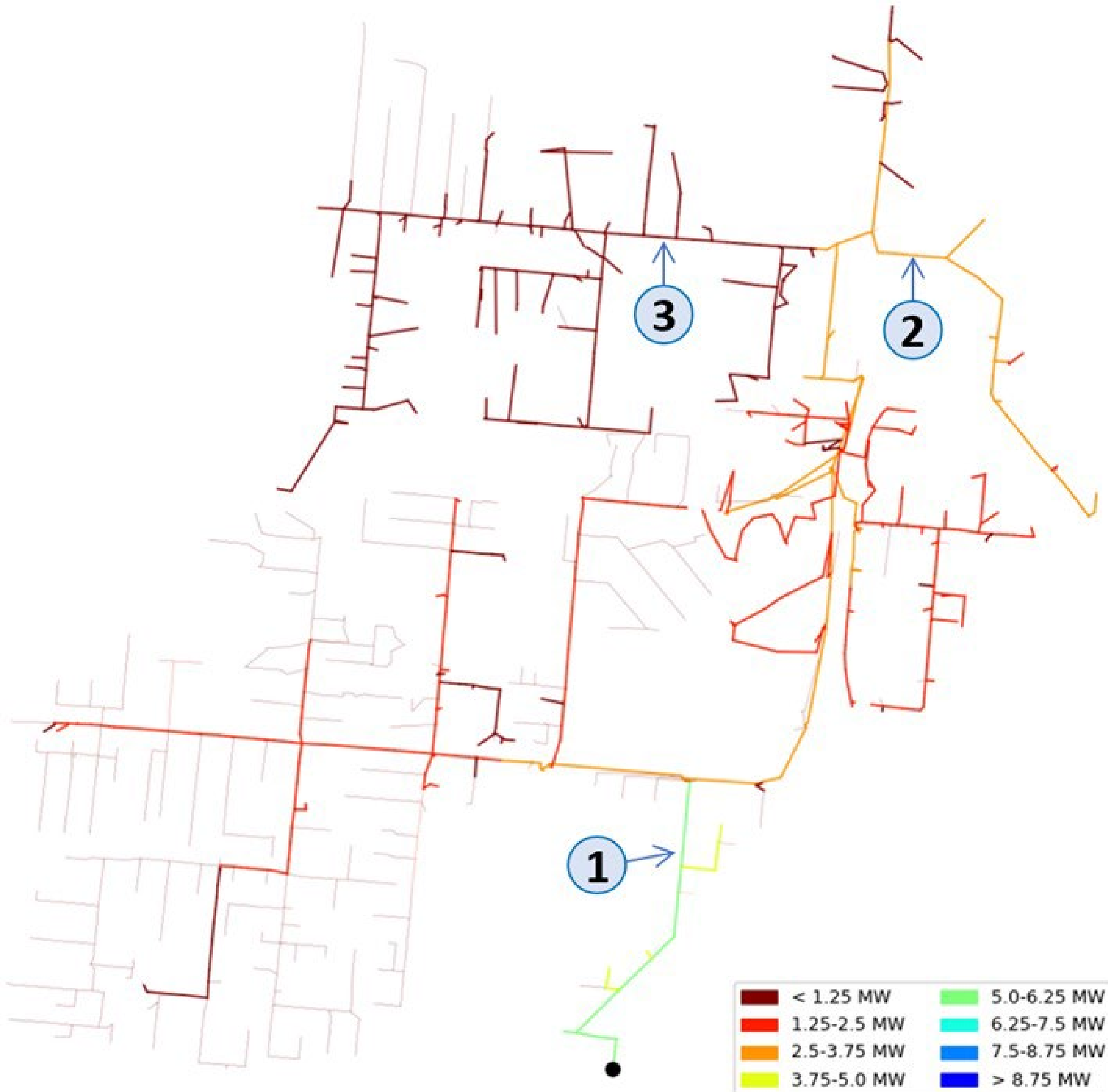


Figure II.1.1 Hosting capacity results for one of the distribution feeders. Source: EPRI analysis

This analysis can be performed across multiple feeders to do a wide-area distribution assessment, as shown in Figure II.1.2. This enables distribution planners to holistically assess the capability of a system instead of focusing on a single feeder at a time. Such an assessment enables planners to identify feeders that are more limited in capacity to prioritize infrastructure investments or feeders with available capacity to potentially incentivize early electrification transition adopters. For instance, feeders 3 and 4 would be good candidates for hosting large depots of EVs, whereas feeders 1 and 7 would not, as they have limited capacity.

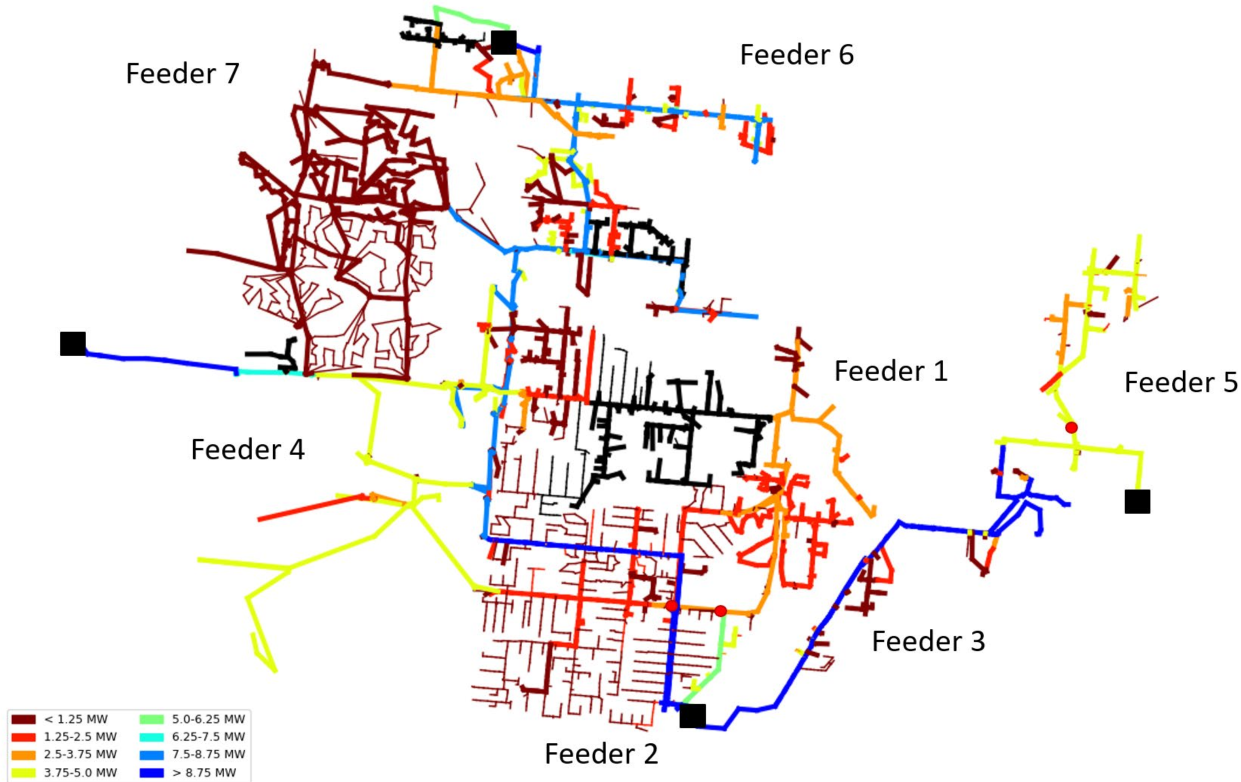


Figure II.1.2 Wide-area distribution assessment – hosting capacity. Source: EPRI analysis

Time-Series Hosting Capacity Analysis

Hosting capacity, by definition, estimates the maximum amount of new load that a location can accommodate without experiencing any constraints under the worst-case conditions (i.e., peak load flow). However, peak load condition may occur only a few times a year, and there may be more capacity available during those times. With traditional load growth (e.g., new building construction), distribution planners would always plan with the peak load condition because of the assumption that load growth would exacerbate the peak demand on the feeder. However, the demand from EVs may not manifest itself exactly during peak demand, especially when vehicles could be charged overnight. Hence, there is a growing need to assess grid capability at other time instances to nuance the hosting capacity during peak load condition.

Using grid data, a time-series hosting capacity analysis can be performed to evaluate the available capacity throughout the year at each location on the feeder. Figure II.1.3 shows the hosting capacity map for the same distribution feeders with the time-series hosting capacity at three locations. Note that the lowest value in the time-series plots represents the worst-case condition (peak load) where the hosting capacity is most limiting, which corresponds to the color in the heat map. Furthermore, note how the hosting capacity varies throughout the year; significant capacity may be available at other times during the year.

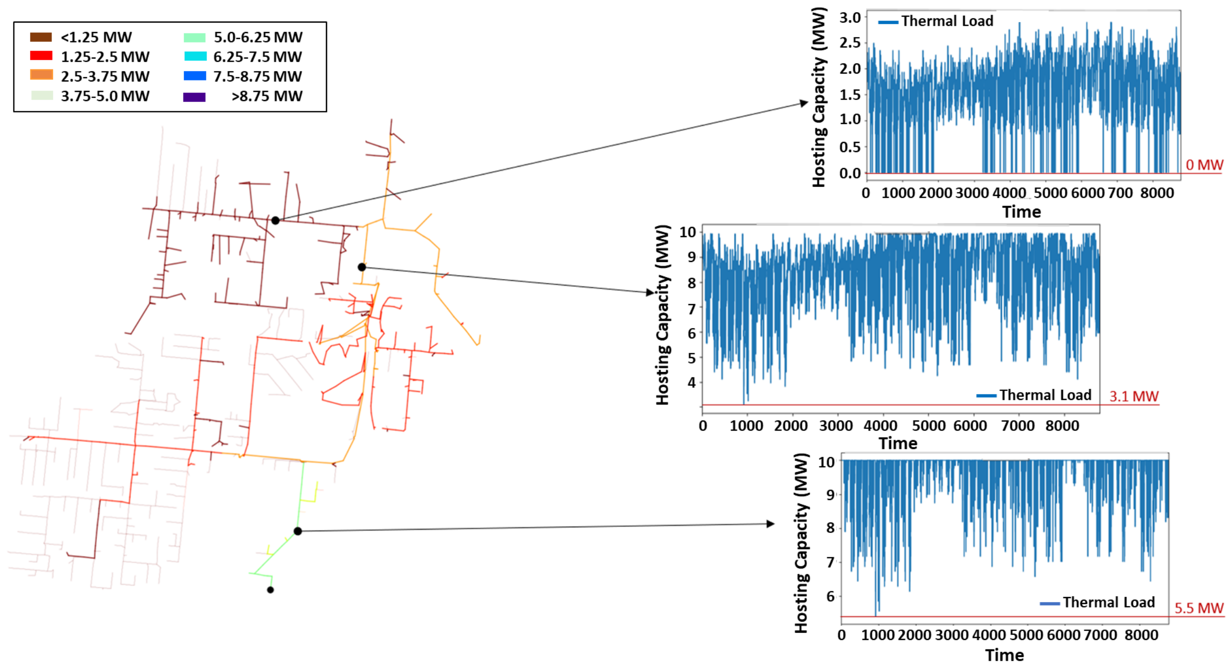


Figure II.1.3 Time-series hosting capacity highlighting three locations on a feeder. Source: EPRI analysis

Conclusions

The technology transfer workshop was successfully held. The report is written and expected to be complete in FY 2024.

Acknowledgements

The team would like to acknowledge the help of Project Officer Jonathan Kung of the National Energy Technology Laboratory, the technical contributions of Jeremiah Deboever of EPRI, and the technical contributions of Brennan Borlaug and Matteo Muratori of the National Renewable Energy Laboratory.

II.2 Integrated Modeling and Technoeconomic Assessment of Electric Vehicle Community Charging Hubs (University of Illinois)

Eleftheria Kontou, Co-Principal Investigator
University of Illinois Urbana–Champaign
205 N. Mathews Avenue
Urbana, IL 61801
E-mail: Kontou@illinois.edu

Yan (Joann) Zhou, Co-Principal Investigator
Argonne National Laboratory
9700 South Cass Avenue
Lemont, IL 60565
E-mail: YZhou@anl.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: October 1, 2020	End Date: December 31, 2024	
Project Funding (FY23): $388,900	DOE share: $350,000	Non-DOE share: $38,900

Project Introduction

In urban areas, parking management emerges as a critical issue, raising concerns related to environmental and congestion externalities. Increased bottlenecks, vehicle emissions, fuel consumption, and pedestrian safety concerns are associated with spending more time searching for parking in city centers. At the same time, a sparse network of parking spaces equipped with electric vehicle (EV) charging infrastructure poses a challenge to EV owners [1]. Urban parking facilities often fail to provide an adequate number of charging stations for EVs. Limited chargers in urban parking facilities hinder the accessibility of convenient public charging options [2]. The absence of urban destination charging can discourage the widespread adoption of EVs, as prospective owners are deterred by the unavailability of reliable and easily accessible charging infrastructure.

Shared parking and its management enable multiple users or businesses to share the same parking area, maximizing the utilization of available parking spaces [3]. This project's research centers on the management of shared parking and EV charging infrastructure within multi-unit dwellings (MUDs). In our previous studies [4], [5], we uncovered that many private parking spaces and EV charging stations within MUD parking lots remain available during the daytime because their residents typically commute by car, resulting in low charging utilization rates. The average maximum utilization rate of charging infrastructure in MUDs is only about 29% [4]. Given that the installation and use of home chargers in MUDs can be hindered by capital and installation cost burdens [6], the implementation of shared parking and charging management within MUDs presents a potentially viable business model, in mixed land use, where businesses, workplaces, and residences coexist. Such a concept allows for increased utilization of parking spaces and chargers within MUDs, generating revenue that can help alleviate parking maintenance and charging installation cost burdens.

We model a shared parking and EV charging reservation and allocation system for MUD charging hubs and public users/commuters to demonstrate opportunities to provide accessible parking and charging services to the public. Our framework models both parking and charging supply objectives and demand choices. To accommodate both electric and gasoline vehicles' parking and/or charging requests, a binary integer linear programming model, incorporating a set of matching rules, is formulated. Counterfactual analysis is conducted to model EV charging behavior. The results of numerical experiments, conducted in a neighborhood of Chicago, Illinois, using real-world data, are presented to demonstrate the effectiveness of the proposed system.

Objectives

Our objective is devising a shared parking and charging management system, aimed at increasing the utilization rate of MUD parking and EV charging and, to some extent, alleviating the difficulties drivers face in finding parking spaces and charging infrastructure in urban centers and mixed land use-built environments. On the supply side, we propose a binary integer linear program (BILP) to allocate parking and EV charging requests to available parking spaces in MUDs, including those equipped with chargers. The model incorporates matching rules to handle scenarios involving a mix of parking and EV charging requests. On the demand side, we conduct counterfactual analysis to derive a charging choice model using empirical data. The model is fitted leveraging variables such as charging duration, distance from a proxy destination, number of charging stations at a location, and total charging and parking cost. Our management model and its proposed heuristic algorithmic solution are applied to a neighborhood of Chicago, Illinois, and assess its performance compared to a first-come-first-served (FCFS) strategy and optimal results derived by commercial solvers.

Approach

Shared Parking and Charging Management Approach in MUD Parking Lots

Our proposed framework, illustrated in Figure II.2.1, models users' demand and MUD parking and charging reservation and management practices. Each MUD parking/charging facility and EV driver are considered as utility maximizing entities, aiming to maximize revenue and minimize costs, respectively. Each MUD parking lot has two types of parking spaces: regular ones and spaces equipped with EV chargers. MUD parking management receives two types of requests: concurrent parking and charging requests or parking-only requests. The MUD manager solves a BILP model to maximize revenue, based on the available parking and charging supply and demand information, and allocates the requests to appropriate parking and charging spaces. To account for the mix of electric and gas vehicles requests, the BILP model incorporates a set of matching rules. For the drivers, the decision-making process involves selecting a suitable MUD parking lot based on a choice model that takes into consideration both supply and demand information. To obtain realistic results, we fit the user's choice model by conducting a counterfactual analysis and observing charging choices. To capture the dynamic nature of the system and address inherent uncertainties, we have designed the system as a dynamic one, implementing a rolling horizon strategy to replicate the entire process.

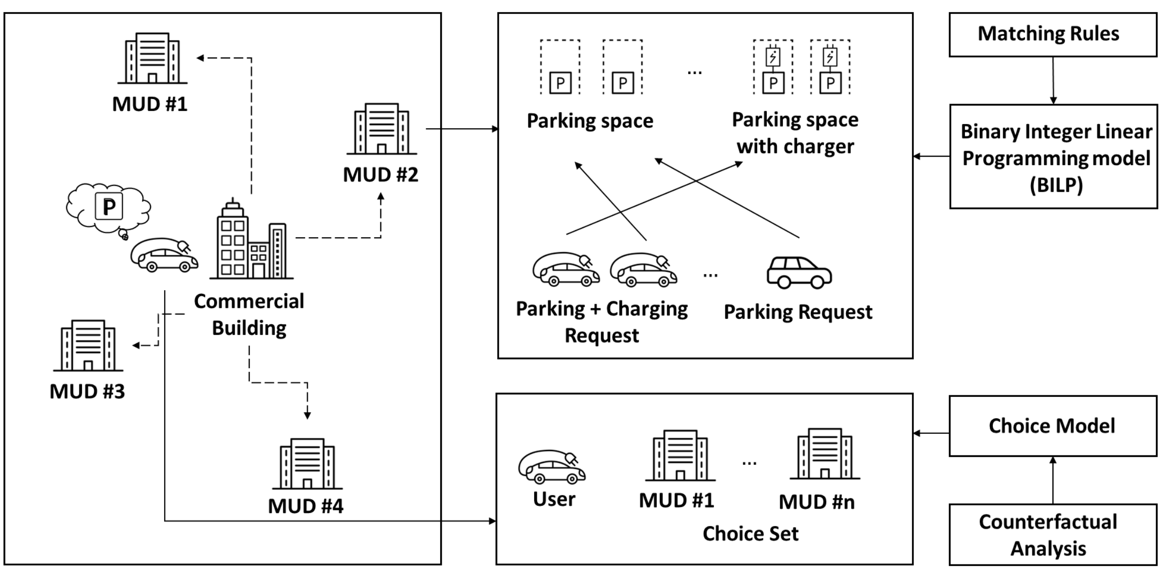


Figure II.2.1 A schematic of our shared parking and charging management approach in MUD parking lots. Source: University of Illinois Urbana-Champaign (UIUC)

Numerical Experiments

To illustrate our findings, we focus on the Englewood community of Chicago, Illinois. Englewood consists of 10 commercial cluster centroids shown in Figure II.2.2(a) and 20 MUD cluster centroids shown in Figure II.2.2(b). Drivers visiting the commercial cluster centroids for work or leisure purposes can utilize nearby MUDs to find parking spaces or charging infrastructure. The sharing period for these facilities is from 9:00 AM to 5:00 PM, with the system reassigning parking requests every ten minutes. In our analysis, we consider Level 2 charging stations with a power rating of 6.6 kW. To ensure adequate supply and demand, we set the ratio of parking spaces with chargers to the total supply and the ratio of charging requests to the total demand to 0.5. Reservation requests follow a Poisson distribution, while the duration of parking follows a negative exponential distribution with an average of 120 minutes [3].

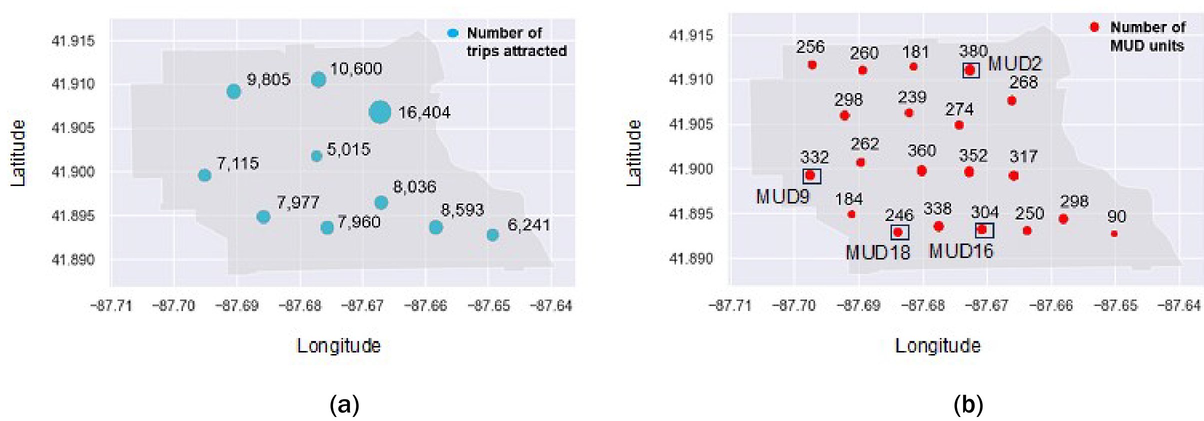


Figure II.2.2 Clustering results of (a) commercial and (b) MUD-family residential land uses in Englewood of Chicago, Illinois. The number of trips attracted and the number of MUD units are indicated by the size of the marker in (a) and (b), respectively. Source: UIUC

Results

Choice Model

We fit a charging choice model from a sample of 63,411 charging events. Table II.2.1 depicts the outcomes obtained from the choice model for a subset of commercial destinations. We observe that drivers typically opt for multi-unit residential area parking and charging facilities that are either closer to their destinations or offer lower overall fees. For example, the third row of Table II.2.1 shows drivers whose destination is commercial centroid 1. The drivers' initial choices include MUDs 2, 9, 16, and 18. Notably, MUD 9 emerges as the closest option to commercial centroid 1, and MUDs 2, 16, and 18 offer the lowest combined sum of reservation, parking, and charging fees. A significant portion of drivers opt for MUD 2, which offers the lowest fee among the available options. By the 36th optimization time, there is a significant decrease in the share of drivers selecting MUD 2. To illustrate this, consider drivers whose destination is location 0 (see the second row of Table II.2.1). The share of drivers choosing MUD 2 decreases from 91% to 33%. This decline can be attributed to increased parking utilization of MUD 2 that leads to an increased reservation fee, since the fee is a function of parking utilization. Consequently, the fee in MUD 2 is no longer the lowest compared to other available MUDs. As a result, at this point in the modeling horizon, drivers opt for alternative MUD parking and EV charging facilities.

Table II.2.1 Results of The Charging Choice Model for a Subset of Commercial Destinations

Commericial Destination	Optimization Time 1~35		Optimization Time 36		Optimization Time 37		Optimization Time 38~53	
	MUD Residential Area #	Share (%)	MUD Residential Area #	Share (%)	MUD Residential Area #	Share (%)	MUD Residential Area #	Shar e (%)
0	2 11	91 9	2 11 16	33 16 51	2 11 16	15 23 6	2 11 16	15 23 62
1	2 9 16 18	32 35 31 2	2 9 16 18	5 35 48 11	2 9 16 18	5 35 48, 11	2 9 16 18	5 35 48 11
7	2	100	2 16	64 36	0 2 11 16	21 23 1 55	0 2 11 15 16	24 17 1 3 55
9	2 16 17	27 62 11	2 16 17	5 83 11	2 16 17	5 83 11	2 16 17	5 83 11

Parking and Charging Allocation Results for Each Multi-Unit Dwelling

Figure II.2.3 illustrates the number of matchings as a system performance metric. We consider four additional metrics: the number of matched charging requests, parking utilization, charging utilization, and revenue for five selected MUDs: MUD 0, MUD 1, MUD 2, MUD 9, and MUD 16. These five MUDs are chosen as representatives of our analysis. MUD 0 represents MUDs that initially do not receive any visits but start to be utilized once the occupancy rates of other MUDs become high. MUD 1 represents MUDs that are not visited throughout the simulation period. MUD 2 emerges as the most popular choice due to its lower fees, resulting in an influx of requests at the beginning, quickly reaching its saturation point. The saturation point occurs when parking utilization rates reach a threshold where the dynamic fee will significantly increase. MUDs 9 and 16 are compared to MUD 2. MUD 9 receives fewer requests than MUD 2, while MUD 16 receives a similar number of requests to MUD 2, but the values of each metric change in a distinct manner, as discussed below.

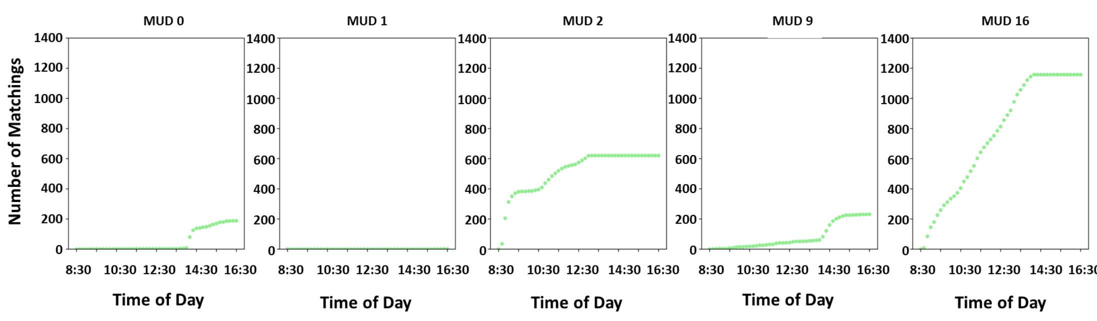


Figure II.2.3 Overview of the number of matchings per time of day, one of the MUD parking and charging management system metrics, for a subset of representative MUDs. Source: UIUC

The rate of increase of the number of matchings varies across different MUDs, occurring at different times. For instance, MUD 0 and MUD 9 number-of-matchings slope is steepest around 14:00, while MUD 2 exhibits its fastest growth at approximately 8:30 (at the initial stage). MUD 2, being the preferred choice for most drivers, attracts a high volume of requests right from the beginning, leading to a swift increase in all five metrics' values. Once the occupancy rate of MUD 2 reaches a threshold, drivers begin selecting an alternative MUD lot (e.g., MUD 0 and MUD 9), resulting in a subsequent increase in these MUDs' metrics.

We compare the results for MUD 2 with MUD 16: even though the latter accepts more requests in the last iteration (621 requests for MUD 2 and 1,158 requests for MUD 16), it generates less revenue. This can be attributed to two primary factors. First, MUD 2 exhibits a higher charging utilization rate compared to MUD 16. As more charging stations are occupied, a greater amount of charging fees can be collected, contributing to a higher revenue. Second, there is a distinction between MUD 2 and MUD 16 in the parking duration of the accepted requests. On average, MUD 2 drivers are parked for longer periods than MUD 16 ones. Drivers with longer parking durations are more sensitive to fees, as indicated by the choice model. Therefore, users with longer parking duration choose MUD 2 over MUD 16. This phenomenon also explains why MUD 2 generates more revenue than MUD 16. The aforementioned factors contribute to the observed difference in revenue between MUD 2 and MUD 16, despite MUD 16's accepting a greater number of requests.

Comparison between First-Come-First-Served and Optimal Results

We conducted a comparison between our proposed framework, an FCFS strategy, and the optimal results to assess the effectiveness of our approach. We focused on evaluating the performance of MUD 2 in terms of four key metrics: number of matchings, parking utilization, charging utilization, and revenue. The metrics for MUD 2 are shown in Figure II.2.4(a-d). The FCFS strategy entails accepting a request at a MUD if it can be accommodated and rejecting it otherwise. This process is repeated throughout the simulation until its conclusion. The optimal results are obtained by solving a BILP model, assuming complete knowledge of all requests in advance.

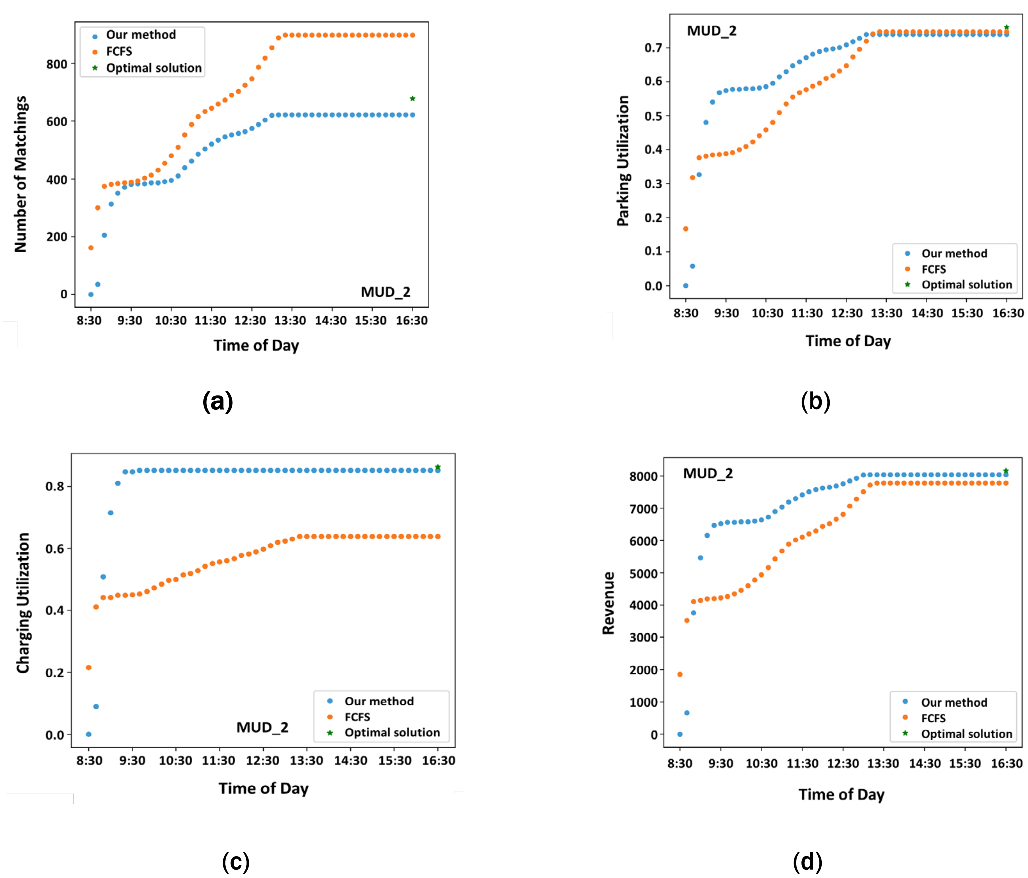


Figure II.2.4 Comparison on four management performance metrics [(a) number of matchings, (b) parking utilization, (c) charging utilization, and (d) revenue] of the proposed framework with a FCFS scheme and the optimal solution (assuming all demand is known in advance). Source: UIUC

The FCFS strategy yields a higher number of matched requests compared to our proposed method. In fact, the number of matches achieved through FCFS even surpasses the optimal results. Note that the optimal results are obtained when maximizing the MUD's revenue, similar to our method. Our method has a consistently higher parking utilization rate, outperforming the FCFS strategy until the time of day at approximately 13:00. Beyond this point, the parking utilization rate of our method remains unchanged, while it increases for the FCFS strategy. This shift in this performance metric can be attributed to the implementation of our dynamic reservation fees. When the parking utilization rate reaches a certain point, the reservation fee has a significant increase. When this threshold is reached, users are deterred from selecting MUD 2 as their preferred choice. This explains why, after a certain time, the parking utilization rate for our method remains stagnant, while the FCFS strategy gains an advantage. Furthermore, it is noteworthy that both the FCFS strategy and our method exhibit results that are closer to the optimal results in terms of parking utilization rate.

Our method demonstrates significantly higher charging utilization compared to the FCFS strategy, closer to the optimal results. Accepting a greater number of charging requests leads to higher revenue generation, which is our objective. As a result, our method prioritizes accommodating charging requests, contributing to a higher charging utilization rate. At the same time, the BILP model incorporates matching rules that give priority to charging requests over parking requests. These matching rules are designed to improve the utilization of charging stations. Consequently, our method results in a higher charging utilization rate compared to the FCFS strategy. The combination of revenue maximization and the integration of charging-specific matching rules in our BILP model and management approach contributes to achieving the management's goals for revenue maximization but also increasing the charging utilization rate.

Conclusions

During the daytime, the availability of vacant parking spaces and EV charging infrastructure in MUDs can address the limited network of public parking and charging options in urban, mixed-land-use areas. Our research evaluates the feasibility of a shared parking and charging system in MUDs, catering to the public, given that our prior work addressed modeling of evening/overnight MUD residential charging management [4]. The effectiveness of our management system is demonstrated through its application in a neighborhood of Chicago, Illinois. We assess its performance using various metrics, comparing it to an FCFS strategy and optimal results derived from a commercial solver.

Through our research, we devise both parking management and EV charging behavior models, thereby offering holistic insights derived from commercial shared parking and charging in MUDs. By evaluating various performance metrics, our approach proves to be more effective, in terms of revenue and charging utilization, than the FCFS unmanaged strategy. Our method achieves results that are also close to optimal outcomes. Although our numerical experiment is limited to a neighborhood of Chicago, other neighborhoods and cities can readily adopt our model since it is transferable. The sensitivity analysis investigates the system's performance in terms of revenue maximization, request rejection, and supply and demand balance. Our findings can guide MUD managers and residents in selecting the most appropriate parameter values based on their specific objectives and priorities.

Key Publications

1. Cheng, X., and E. Kontou. 2023. "Estimating the electric vehicle charging demand of multi-unit dwelling residents in the United States." Environmental Research: Infrastructure and Sustainability, 3(2), 025012.

2. Zhang, R., N. Horesh, E. Kontou, and Y. Zhou. 2023. "Electric vehicle community charging hubs in multi-unit dwellings: Scheduling and techno-economic assessment." Transportation Research Part D: Transport and Environment 120, 103776.

3. Zhang, R., and E. Kontou. 2024. "Revenue maximizing shared parking and electric vehicle charging management in multi-unit dwellings." Accepted for presentation at the 2024 Transportation Research Board Annual Meeting.

References

1. Sadreddini, Z., S. Guner, and O. Erdinc. 2021. "Design of a decision-based multicriteria reservation system for the EV parking lot." *IEEE Transactions on Transportation Electrification* 7(4): 2429–2438.

2. Wood, E. W., C. L. Rames, M. Muratori, S. Srinivasa Raghavan, and M. W. Melaina. 2017. "National plug-in electric vehicle infrastructure analysis." NREL/TP-5400-69031; DOE/GO-102017-5040, National Renewable Energy Laboratory (NREL), Golden, CO.

3. Shao, C., H. Yang, Y. Zhang, and J. Ke. 2016. "A simple reservation and allocation model of shared parking lots." *Transportation Research Part C: Emerging Technologies* 71: 303–312.

4. Zhang, R., N. Horesh, E. Kontou, and Y. Zhou. 2023. "Electric vehicle community charging hubs in multi-unit dwellings: Scheduling and techno-economic assessment." *Transportation Research Part D: Transport and Environment* 120, 103776.

5. Cheng, X., and E. Kontou. 2023. "Estimating the electric vehicle charging demand of multi-unit dwelling residents in the United States." *Environmental Research: Infrastructure and Sustainability* 3, 025012.

6. Ge, Y., C. Simeone, A. Duvall, and E. Wood. 2021. "There's no place like home: residential parking, electrical access, and implications for the future of electric vehicle charging infrastructure." NREL/TP-5400-81065. NREL, Golden, CO.

Acknowledgements

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II.3 Micromobility Screening for City Opportunities Online Tool (University of Washington)

Don MacKenzie, Principal Investigator
University of Washington
Box 352700
Seattle, WA 98195-2700
E-mail: dwhm@uw.edu

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: October 1, 2020 End Date: September 30, 2023
Project Funding (FY23): $337,008 DOE share: $299,628 Non-DOE share: $37,380

Project Introduction

Micromobility (personal mobility modes based on very small vehicles, typified by bike-sharing and scooter-sharing) boomed following the introduction of dockless services in 2017–2018, as companies flooded U.S. cities with scooters and bikes. The industry then entered a phase of rationalization in search of profitability, even as many cities scrambled 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 allows 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 was 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) is 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 integrates new and previously collected data to evaluate and display the market potential, accessibility, energy productivity, and emissions savings associated with micromobility services. The framework is readily adaptable to alternative models of trip generation and mode choice, diverse levels of geographic aggregation, and user-specified assumptions about the cost and availability of micromobility vehicles. The modeling system has been implemented in an online tool accessible to the public, and the underlying code is open source to facilitate further development.

Approach

The overall structure of the SCOOT modeling framework is illustrated in Figure II.3.1. The work to develop SCOOT involved the following activities:

- Gathering necessary background information, including a review of prior research on the determinants of micromobility ridership and an inventory of publicly available data sources to support model development and calibration.
- Designing, programming, and administering a web survey, which included a stated preference / revealed preference (SP/RP) choice experiment designed to elicit preferences for features such as walking access time, waiting time, travel time, and the effects of bike lanes on willingness to use

micromobility. Usable responses from 1,774 individuals across the United States were used to estimate models of mode choice.

- Generating a synthetic population sample for each census tract in the United States using data from the American Community Survey (ACS). The samples were generated such that they matched the real tracts in their distributions of age, gender, income level, and education level.
- Modeling tours and destination choices using National Household Travel Survey (NHTS) data to generate daily travel activities for individuals in the synthetic population sample.
- Integrating the tour generation and mode choice models into the SCOOT framework; applying them to each individual in the synthetic sample to predict the utility of each mode and the number of micromobility trips.
- Calculating the accessibility, greenhouse gas (GHG) emissions, and mobility carbon productivity (MCP) effects of the micromobility modes at the census tract level.
- Calibrating model outputs against micromobility demand observed in the real world.
- Deploying SCOOT as an online, publicly available web tool.

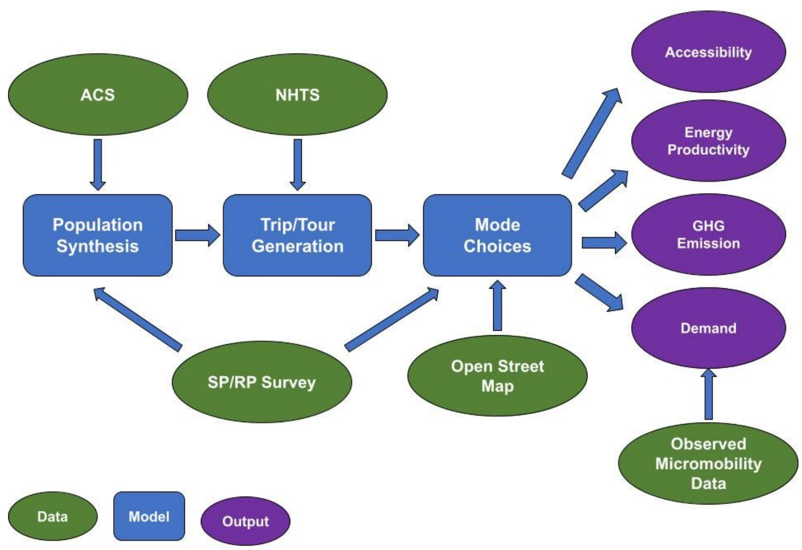

Figure II.3.1 Overview of SCOOT analytical framework. Green = data sources; blue = key modeling tasks; purple = key outputs. Source: University of Washington

Results

The SCOOT online mapping tool ties the SCOOT analytical framework to a web-based interface that allows users to specify assumptions about implementation location, price, vehicle density, and bike lane availability. The results from the analytical tool are fed to a reporting interface that maps key measures of micromobility performance—including daily total number of trips, accessibility, MCP, and GHG emissions—at tract level for all MSAs in the United States.

The mapping tool is implemented in R Shiny and hosted on a Shiny server.[1] The SCOOT Shiny application has three main components: (1) a user interface object that sets up the layout of the webpage, (2) a server function that contains a series of reactive functions that retrieve data, calculate and aggregate for reporting metrics, and create maps and plots for the final results based on the input and output of the mapping tool, and (3) a call to the Shiny application function. Because applying the SCOOT framework to an MSA can take more than ten minutes to run, the project team pre-simulated each MSA's population and daily trips, estimated each simulated individual's mode choices, and stored all data in an Amazon Web Services (AWS) database. We then established a connection between R Shiny and AWS to retrieve data needed to calculate micromobility performance metrics to enable real-time visualization.

A demonstration of the tool can be accessed through https://stlab.shinyapps.io/scoot_shiny/.

Figure II.3.2 shows a screenshot of the dashboard. On the side panel, users can choose the MSA of interest; specify four population density levels where micromobility is to be implemented (i.e. everywhere, only in tracts with population density above 5,000 per square mile, above 10,000 per square mile, or above 20,000 per square mile); vary the price of micromobility services[2] (i.e., \$0.15/min,\$0.25/min,\$0.35/min); adjust access and drop off walking time (i.e., 1 min, 3min, 5 min); and toggle bike lane availability (i.e., less than 80% of the whole trip, more than or equal to 80% of the whole trip). Then users can choose which micromobility services to simulate and which performance metric to display, including trip count[3], net accessibility[4], net MCP[5], and net GHG emissions[6], to be shown on the map on the main panel. Below the map on the main panel, two bar charts show the distribution of net accessibility and net MCP across different income groups.

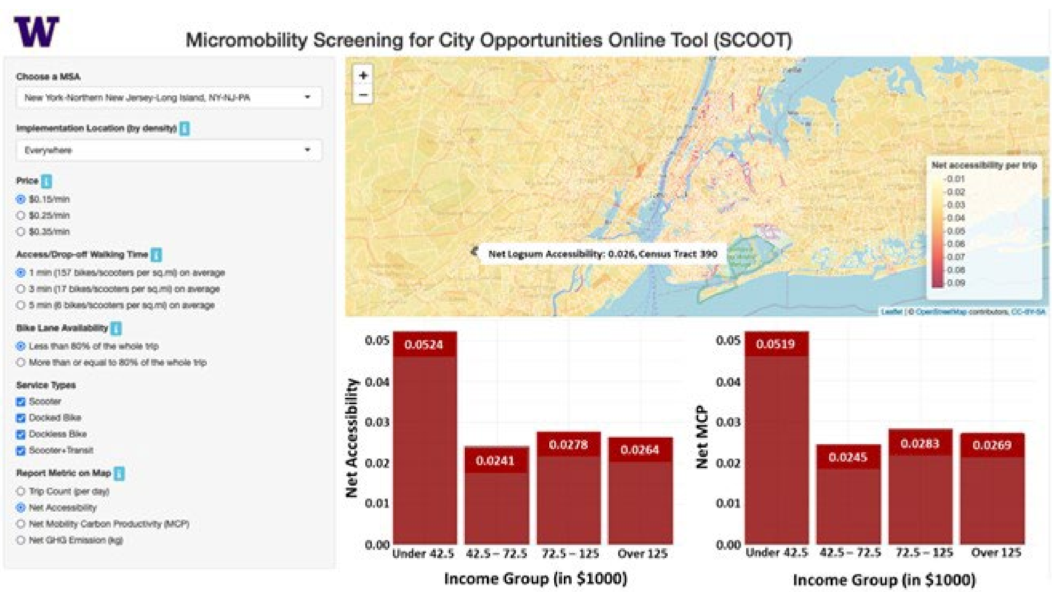

Figure II.3.2 Screenshot of SCOOT web tool interface showing net effects of micromobility services on accessibility. University of Washington

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[1] *Shiny* (website). Accessed 2023. https://shiny.posit.co/r/getstarted/shiny-basics/lesson1/index.html.

[2] Total cost of a trip consists of a \$1 unlocking fee and price per minute x trip time. If a trip is integrated with transit, there will be a \$2 additional transit fee.

[3] Total number of daily trips.

[4] Change in average accessibility per trip after introducing micromobility services.

[5] Change in average MCP per trip after introducing micromobility services.

[6] Change in GHG emissions across all trips after introducing micromobility services.

Conclusions

The SCOOT web tool provides a means to evaluate the effects of micromobility availability and pricing at the census tract level for any MSA in the United States. The underlying code is available for further development by others.

Key Publications

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

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

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II.4 Regional Optimization of Application and Infrastructure Architecture in Heavy-Duty Vehicle Electrification (Oak Ridge National Laboratory)

Vivek Sujan, Principal Investigator
Energy Sciences and Technology Directorate, Oak Ridge National Laboratory
2360 Cherahala Boulevard
Knoxville, TN 37932
E-mail: SujanVA@ornl.gov

Patrick Walsh, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Patrick.Walsh@ee.doe.gov

Start Date: October 1, 2022 End Date: September 30, 2025
Project Funding (FY23): $500,000 DOE share: $500,000 Non-DOE share: $0
Project Funding (FY24-FY25): $1,000,000 DOE share: $1,000,000 Non-DOE share: $0

Project Introduction

For emerging electrified heavy-duty (HD) commercial vehicles (CVs), the energy storage characteristics and refueling infrastructure are a significant departure from today's mature liquid fuel and internal combustion engine systems, presenting a new opportunity and need to co-optimize the development of vehicles, their usage, recharging infrastructure, and the supporting electric grid. Unlike their diesel counterparts, the electrified powertrains present a wide disparity of emerging solutions, requiring that the end user specify the battery and charging infrastructure needed. Energy service providers may not be included in this process. Because of this disconnected effort, CV end users may specify and/or own "behind-the-fence" energy solutions, which drives up asset cost, potential down time, overhead, and net carbon emissions. As charging asset deployment plans progress, organizations are faced with the challenging task of determining the most effective phase-in of this super system. In addition, the grid faces simultaneous challenges of decarbonization, added power capacity requirements from electrification, and the need to reduce the delivered price of electricity.

To address these challenges, this project is developing an optimization tool that brings the battery electric vehicle (BEV) powertrain architecture, charging infrastructure, and grid architecture into a common framework. The goal is to develop deployment roadmaps for HD BEV, charging, and grid infrastructure architectures, with lifetimes spanning 0–10 years. The infrastructure is centered on the intermodal freight transfer points of major U.S. ports, with freight movement radii up to approximately 250 miles.

Roughly 72.5% of the nation's freight is moved by trucks [1], [2]. Shorter-range and/or lower-load cycles for HD CV applications may be well represented by port/terminal drayage missions for intermodal freight transfer and selected hub-spoke missions for general freight movement. Up to 95% of all globally manufactured goods travel in a container at some point [3]. Drayage plays a critical role in moving containers in and out of intermodal hubs, such as shipping ports, harbors, rail terminals, trucking terminals, and warehouses. Altogether, short-haul delivery operations (less than 250 miles per day) constitute about 67% of the trucking freight in the United States [1]. Further, more than 60 million drayage loads are hauled annually [4].

For this research, the analysis and algorithms developed will focus on freight transport by trucks at shipping ports and rail terminals. However, these use cases will be generalized and applicable for all regional hubs/truck transport networks. This is a multi-performer project led by Oak Ridge National Laboratory (ORNL), in partnership with SLAC National Accelerator Laboratory and Ohio State University (OSU), with non-financial support through industry partners Cummins Inc., Walmart Inc., and Tennessee Valley Authority.

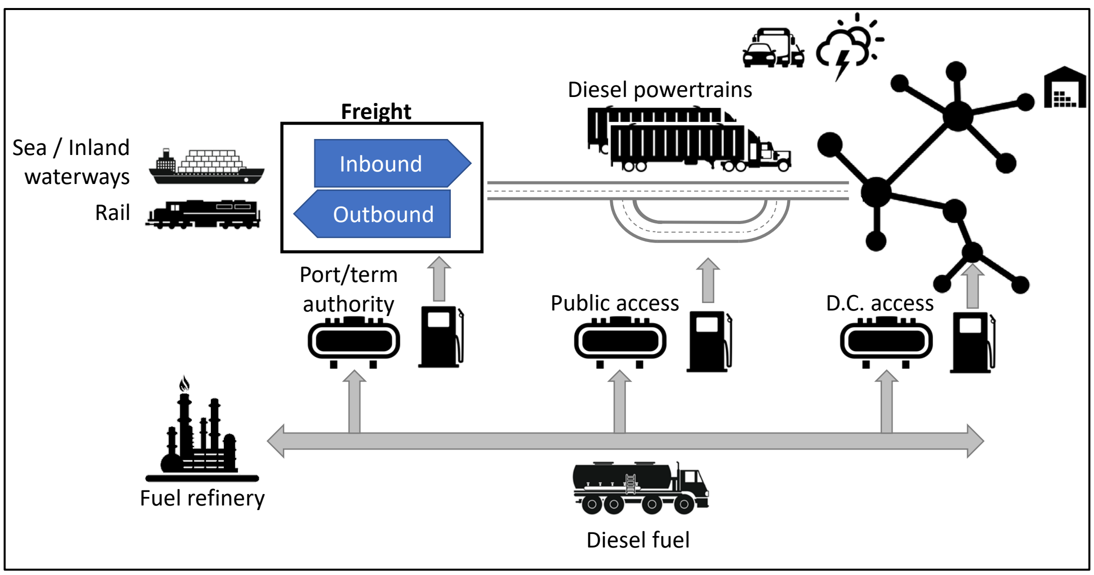
Objectives

This project introduces an innovative analytical framework and solutions that harmonize the often-competing requirements of HD BEVs and the necessary infrastructure. The project formulates a co-optimized scenario-based deployment plan that will serve as a valuable resource for guiding key decision-makers within a fleet, as well as electric grid utilities within this ecosystem, enabling them to proactively address evolving needs and make informed choices. The purpose of this project is to expedite the adoption of HD BEVs, contributing significantly to the decarbonization and sustainable energy practices in the CV freight transportation sector.

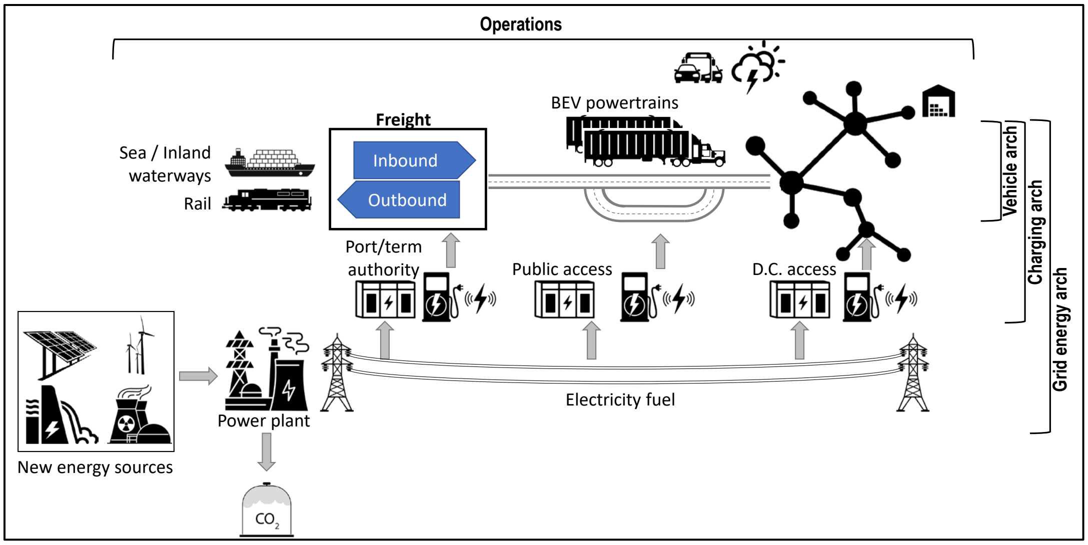
- **Goal 1:** Develop an optimization instrument that brings the CV BEV powertrain architecture, charging infrastructure (both behind-the-fence and public-access), and grid architecture (energy sourcing and carbon management) into a common analytical framework.
- **Goal 2:** Develop technology deployment roadmaps for HD battery electric CVs (at various adoption rates), charging, and grid infrastructure architectures, for freight movement within radii of 50–250 miles, centered on intermodal freight transfer points of all major U.S. shipping ports.

Approach

Figure II.4.1(a) shows a simplified diagram of a conventional shipping port or rail terminal freight trucking network. This constitutes the port/terminal operations, the truck transport vehicles, and the distribution centers/hub. This freight flow system is supported with a diesel fueling infrastructure where vehicle refueling may occur at the ports, on public access roadways, and behind the fence at specific distribution centers. While the operations and coordination of these services is a complex orchestration of several factors, the focus of our research is on the energy pathway and needs for the trucking system.



(a)

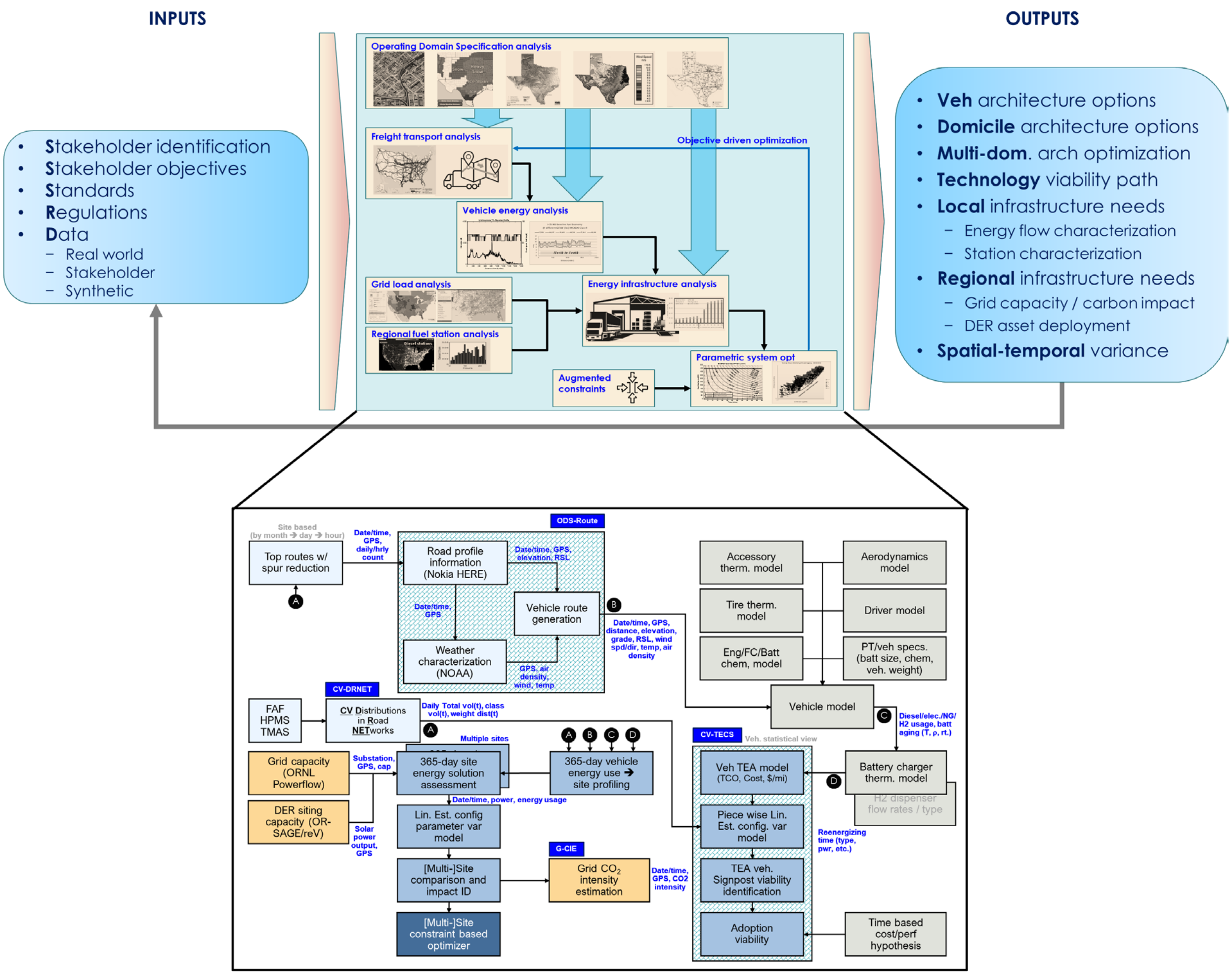


(b)

Figure II.4.1 Freight transport network: (a) current and (b) future/emerging highly electrified. Source: ORNL

Figure II.4.1(b) shows a similar, simplified diagram of an emerging highly electrified freight trucking network. In this system, the freight movement and key stakeholders expect few (if any) changes to the freight flow. However, the supporting three architecture layers—vehicle powertrains, charging infrastructure, and the energy sourcing backbone—will experience significant technology change. A complex array of charging options (including dynamic wireless power transfer), along with temporary energy storage to provide grid resilience, will form the bridge between the vehicle powertrain/energy storage technologies and the electric grid. Local distributed energy resources (DERs) for electricity generation and storage are expected to complement the architecture and support intermitted loads, especially on modern grids that are increasingly reliant on renewable power. The traditional approach to optimizing these three architectural layers typically involves separate assessments, with limited interaction and cross-influence. Moreover, regional and temporal variations are often overlooked when developing architecture and technology roadmaps. This approach can result in suboptimal roadmaps for vehicle-specific battery requirements, charging power levels and availability, and overall grid power generation, all while striving to minimize product proliferation.

Through this research project, ORNL has developed an advanced CV road freight network, energy systems architecture, and system-of-systems analytics termed the Optimal Regional Architecture Generation for Electrified National Transport (OR-AGENT) modeling framework. OR-AGENT was introduced at the 14th International Green Energy Conference [5]. The workflow is shown in Figure II.4.2. Within this framework, we conduct a parametric study that utilizes integrated sub-system data and models encompassing various aspects of electrified vehicle powertrain architecture and dynamics, freight logistics (including vehicle origin destination [OD] data, schedules, and weights), traffic patterns, roadway conditions, weather factors, and energy flow pathways (including grid capabilities, energy storage, dispensing facilities, and DERs). This unique methodology for interconnected systems analysis combines insights from vehicles, operational logistics, and energy pathways. It yields a region-specific, seasonally adapted, and constrained-optimal solution for the architecture of vehicles and infrastructure. This optimization process is guided by technoeconomic metrics aligned with the needs of stakeholders in the system, such as fleet operators, electrified equipment suppliers, energy service providers, utilities, and planning agencies. By employing a defined cost function (e.g., total cost of ownership [TCO]) that reflects the interests of these stakeholders, this approach equips local government bodies, industry end users, energy suppliers, and equipment providers with a versatile planning tool. This tool facilitates the strategic deployment of electrified freight transportation systems, accommodating regional variations and constraints arising from diverse stakeholder motivations within this ecosystem. While conventional analytical methods often consider infrastructure in a piecemeal fashion without accounting for regional nuances, our approach systematically integrates the evaluation, resulting in a coherent and comprehensive roadmap for vehicle and energy infrastructure development. Details of this approach may be found in "Assessing Powertrain Technology Performance and Cost Signposts for Electrified Heavy Duty Commercial Freight Vehicles" [6].



OR-AGENT – An interconnected systems analysis (micro/meso) bottom-up approach to sustainable blueprints for commercial vehicle fleet decarbonization

Figure II.4.2 OR-AGENT workflow construct and key elements overview. Source: ORNL

Results

The focus of Budget Period 1 (BP1) has been to develop and assimilate the models and the OR-AGENT modeling framework. This begins by developing the specific customer use case. Given the large option space of shipping ports, the key ports have been characterized by the value/quantity of freight moving through these ports, as well as the weather variations seen at these ports. Three ports (Savannah, GA; Houston, TX; and Seattle–Tacoma, WA) were selected to represent the median cases. They are a starting point for this research, with other ports being included in future BPs. The Port of Savannah has been used to develop, establish, and calibrate the models and modeling framework.

Route and Environment Modeling

As shown in Figure II.4.3, the first step is to create a vehicle and port operating domain specification (ODS). This includes establishing the vehicle ODs, the routes taken (including grade, road speed, etc.), vehicle weight and dynamic characteristics (drag, rolling resistance, frontal area), the weather conditions (temperature, air density, wind speed/direction, etc.), vehicle counts (to/from the port along each route), and vehicle schedules (departure/arrival times). Data from several different sources are combined to establish this ODS: StreetLight/ Bureau of Transportation Statistics data (for OD, vehicle count, and schedule) [8], Google maps and Nokia HERE databases (for truck route development) [9], [10] data from the U.S. Department of Transportation's Freight Analysis Framework, Highway Performance Monitoring System, and Travel Monitoring and Analysis System (for vehicle weight distributions) [11], and National Oceanic and Atmospheric Administration data (for weather conditions) [12]. To support both this and future research, the broader data has been combined into an automated process such that a rapid ODS may be established for a given port/fleet domicile.

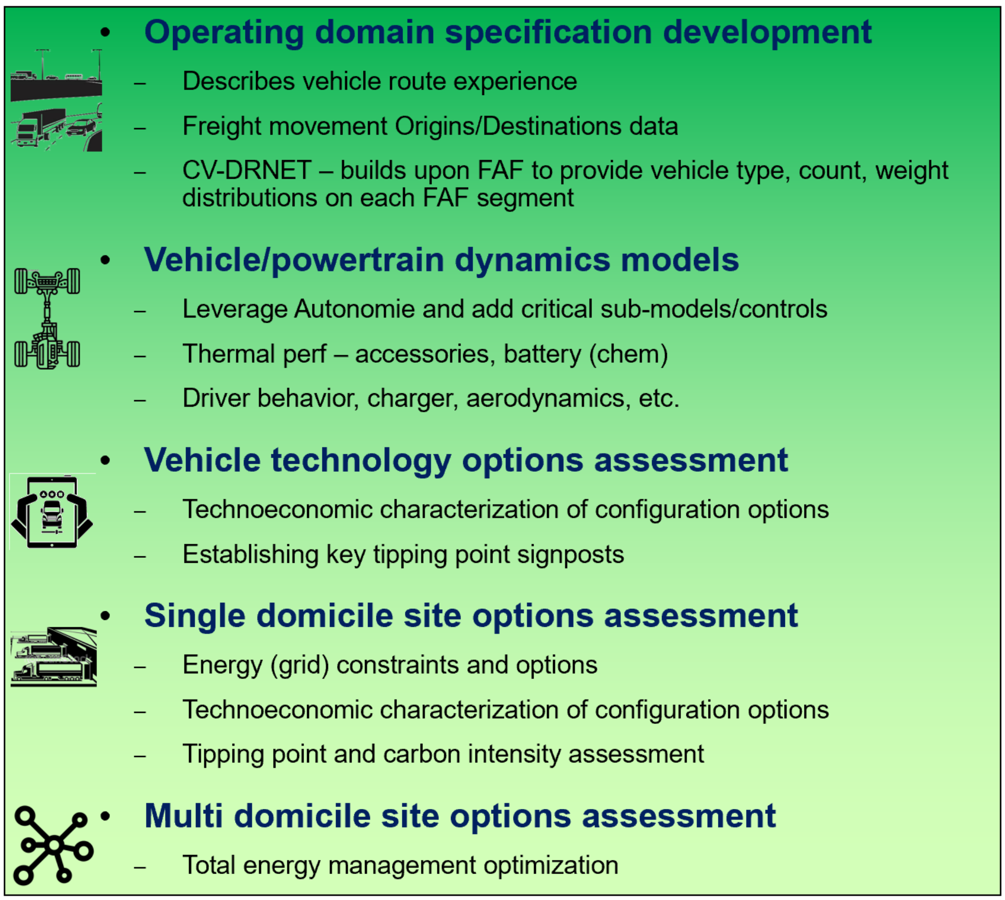
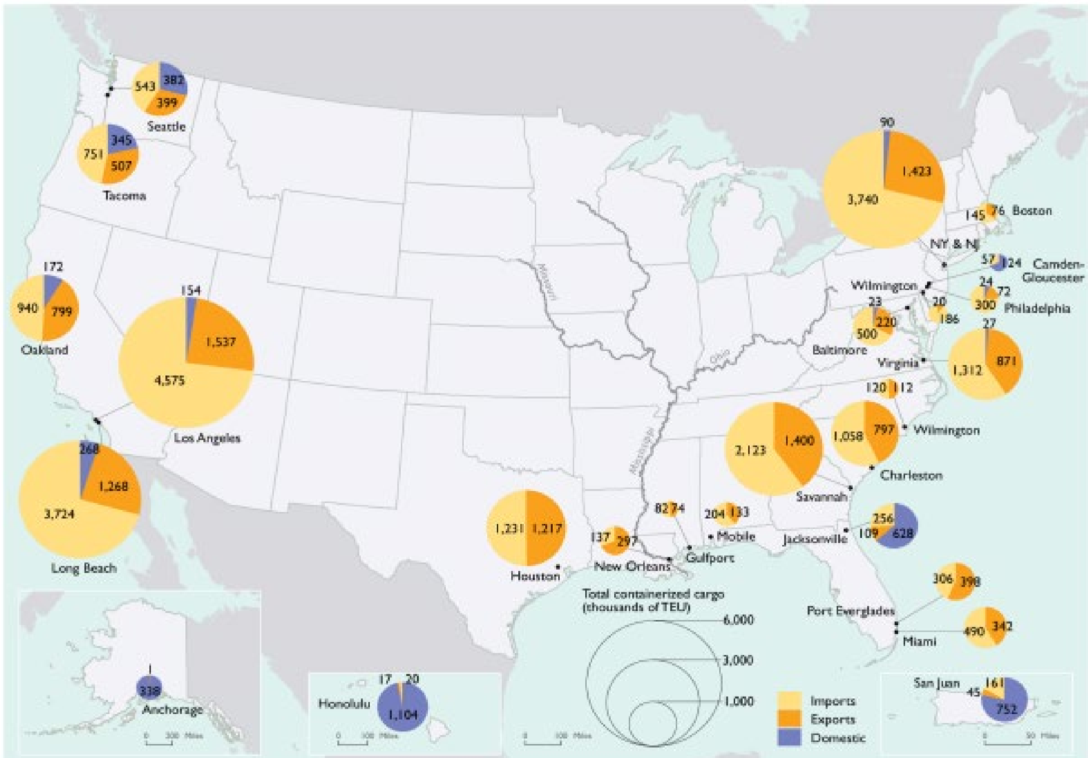


Figure II.4.3 Steps involved in the route and environment modeling. Source: ORNL

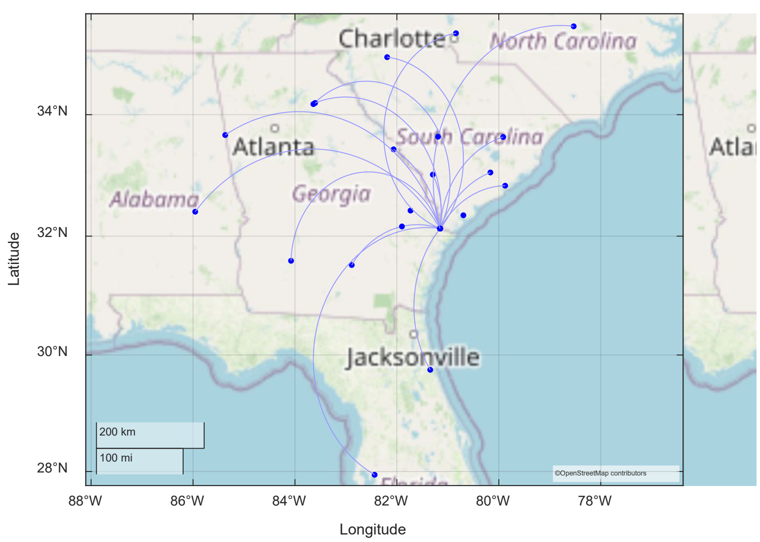
Figure II.4.4 gives an example of the identification and development of vehicle routing at the Port of Savannah that was used in developing the ODS. Of the vehicle miles traveled for drayage, 90% are accounted for in 20 outbound and 21 inbound routes. These 41 routes are modeled over 3 days in each of the 12 months (representing the minimum, maximum, and median temperatures for that month) for a total of 1,476 routes. Additional details on this have been published [5], [6], [13].



KEY: TEU = twenty-foot equivalent unit.

SOURCE: U.S. Department of Transportation, Bureau of Transportation Statistics, based on 2019 data provided by the U.S. Army Corps of Engineers, Waterborne Commerce Statistics Center, special tabulation, accessed November 2020.

(a)



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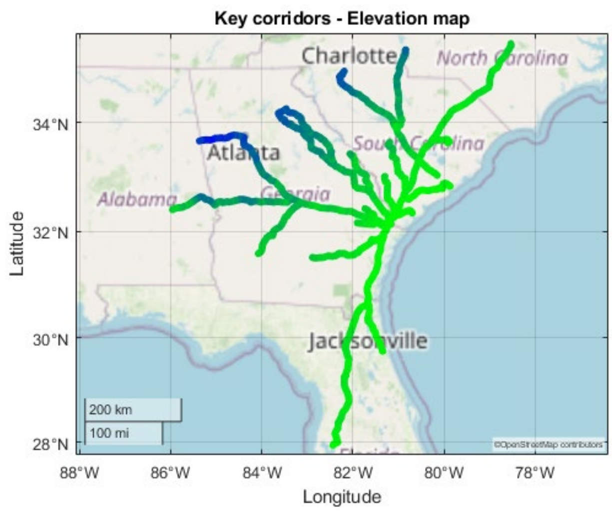

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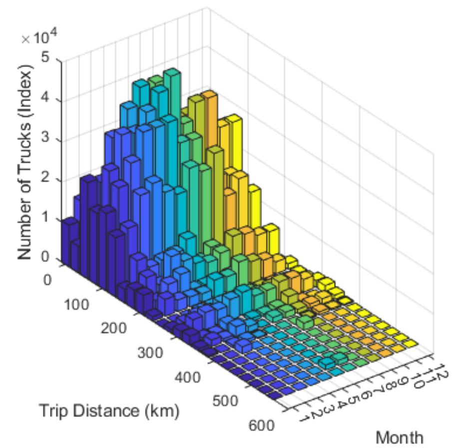
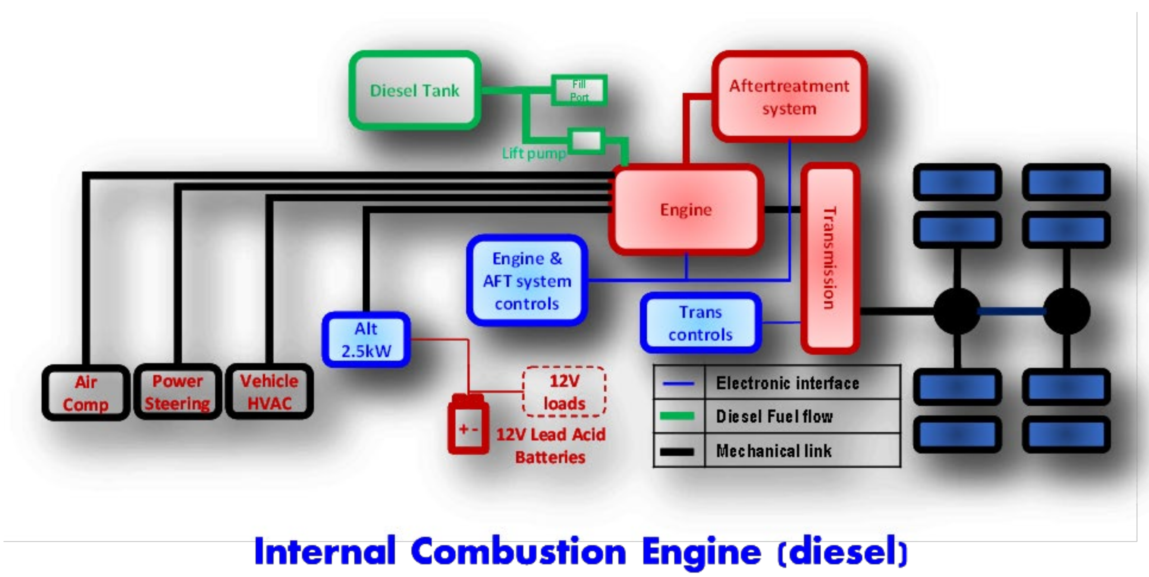


(d)

Figure II.4.4 Identification and development of vehicle ODS at the Port of Savannah: (a) Truck trip origin and destination distribution, (b) origin/destination arcs with trip volume, and (c) key corridors and trip volume based on routing assignments. [7]

Vehicle Modeling

Utilizing road load dynamics, the project has constructed one-dimensional models for the HD diesel powertrain shown in Figure II.4.5(a) and BEV powertrain shown in Figure II.4.5(b). The OSU team worked on developing an advanced vehicle simulator platform on MATLAB/ Simulink to virtually simulate and analyze the energy requirements of electric HD trucks, Classes 9–13 (Federal Highway Administration classification), for real-world routes traveled by drayage trucks. The BEV powertrain architecture is a tandem e-axle configuration with 250 kW electric motors on both axles providing the tractive power to the wheels, as illustrated in Figure II.4.5(b). Each e-axle has an electric motor integrated to a three-speed gearbox, along with gear reductions happening at the axle differential and the wheel ends. This architecture reflects current state-of-the art technology for HD battery electric trucks.



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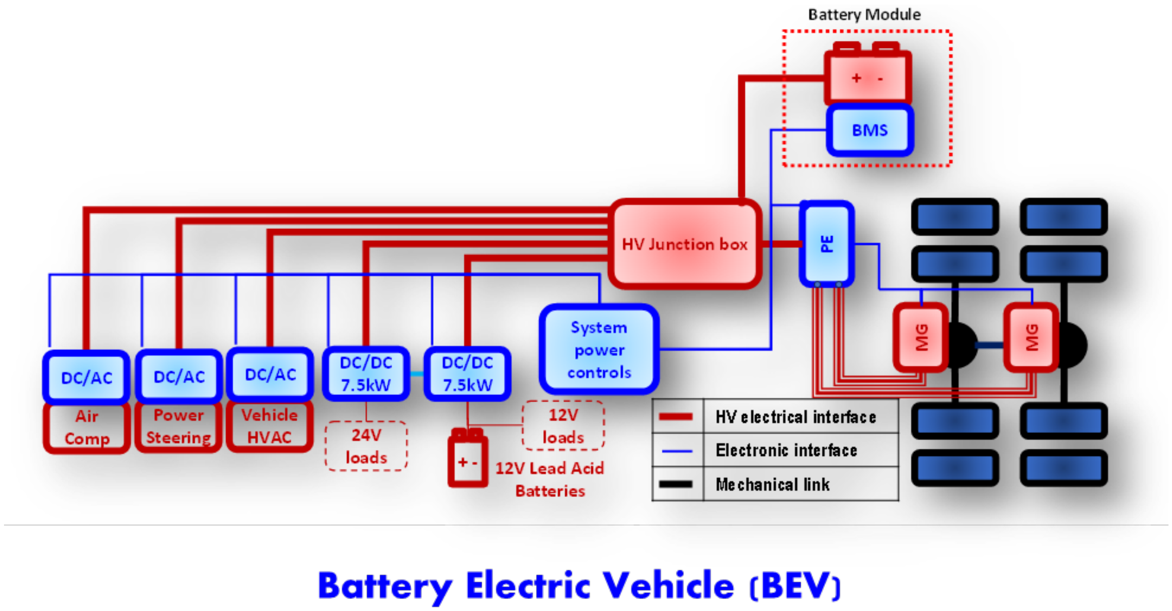
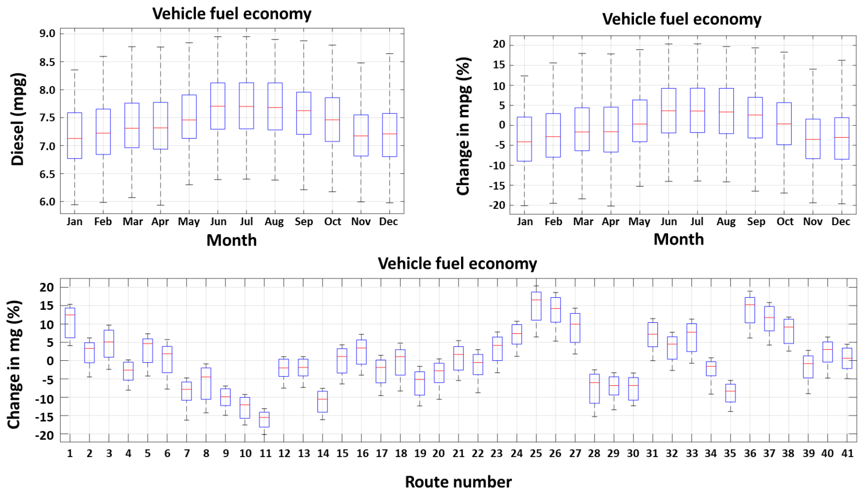


(b)

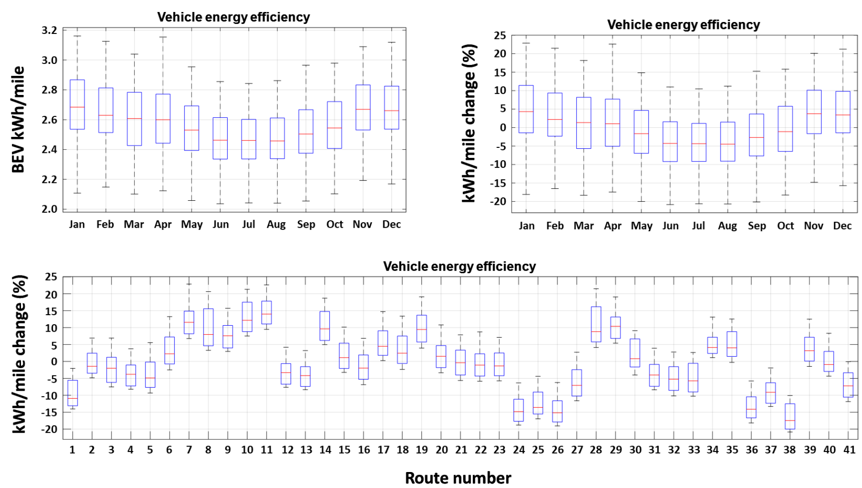
Figure II.4.5 Enhanced powertrain embodiments from (a) diesel powertrain to (b) BEV powertrain for this research project. Source: ORNL

The powertrain is modeled using a forward-looking, quasi-static approach. In a technical paper published in the Society of Automotive Engineers (SAE) International journal [14], Shiledar et al. describe development of a modified enhanced driver model, which is integrated with the simulator to generate a reference speed profile based on the route features (e.g., speed limits and road grade), moving away from fixed drive cycles for greater realism. Shiledar et al. developed a detailed road load model for modeling the resistive forces (aerodynamic and tire rolling resistance) that the truck experiences while in motion. Aerodynamic load modeling accounts for the variation in drag coefficient, based on the truck's configuration (with or without a trailer or container) and the yaw angle relative to the wind direction [15]. The tire rolling resistance model used in the study captures the dependence of rolling resistance coefficient on longitudinal vehicle speed and tire temperature, where the tire thermal dynamics are modeled using a first-order transfer function approximation [16]. The simulator goes beyond the powertrain modeling to include auxiliary components such as the cabin heating, ventilation, and air conditioning compressor, battery thermal management system (BTMS), pneumatic brake pumps, etc. The power consumption modeling of these incorporates a duty cycle-based approach and accounts for the influence of ambient conditions on power usage within the models [17], [18]. The battery and charger models (described below) have been integrated in the vehicle simulator. The integrated model provides the energy consumption of trucks going through the annual seasonal cycle, defined by variations in elevation, grade, ambient temperature, and air density on multiple drayage routes identified at a single freight port. Figure II.4.6(a) illustrates the energy consumption variability over specific routes due to seasonal variations for diesel powertrains and Figure II.4.6(b) for BEV powertrains. The route-based seasonality variations are quantified and show significant changes. These will be validated against real-world data in BP 2. To accommodate the ongoing large scale of this study, a high-performance computing framework that allows multiple parallel simulations on the OSU Ohio Supercomputer is being developed.

Battery Capability and Thermal Management System Modeling



(a)



(b)

Figure II.4.6 Energy consumption variation due to route and seasonality changes (gross combined vehicle weight of 60,000 lbs.): (a) Conventional ➔ minimum: 7.07%, maximum: 13.91%, average: 10.79% ± 1.73% and (b) BEV ➔ minimum: 10.78%, maximum: 17.37%, average: 13.44%± 1.54%. Source: ORNL

Battery Capability and Thermal Management System Modeling

In our work, we aim to capture the capacity and power capabilities of multiple different lithium (Li)-ion battery chemistries at the pack level. To do this, we first calibrate a Li-ion battery cell model that integrates the electrical (using a first-order equivalent-circuit model), temperature (using a first order lumped-parameter thermal model), and aging (using a semi-empirical severity factor-based model) dynamics. Models are calibrated using experimentally collected data (the calibration procedure is detailed in “Electrochemical Techniques and Diagnostics for Lithium-ion Batteries” [19]). The aging dynamics are calibrated using publicly accessible cycle aging datasets, when available; otherwise, we draw from models reported in the literature. To obtain a pack model, the cell model is upscaled by assuming cell-to-cell variations are negligible. In so doing, we reduce the dynamics of a battery pack to those of a single battery cell with scaled inputs and outputs. In BP

1, the project team calibrated models for three different chemistries: lithium nickel manganese cobalt oxide (NMC-811), lithium nickel cobalt aluminium oxide, and lithium-ion manganese oxide.

To understand the effect of cell-to-cell variations in a battery pack, we constructed a model of the battery pack that allows us to track the dynamics of every cell in the pack. Cell-to-cell variations generally can arise from differences in the process manufacturing. The team validated this battery pack model using pack-level experimental data shared with us by Idaho National Laboratory [20]. We find that the effects of cell-to-cell variations can be reduced by having modules with parallel-connected cells. Intuitively, having parallel-connected cells means that the cells within a parallel branch can compensate for any deficiencies of other cells in the branch. This comes at the cost of increased aging for the pack overall; however, this increased aging is lessened when the pack has many parallel-connected cells. Thus, in battery packs that are as large as those found in electrified HD vehicles, neglecting cell-to-cell variations is a reasonable approximation. A manuscript detailing these findings has been submitted for review [21].

One system that consumes a sizable share of energy during vehicle operation is the BTMS. This system is essential to ensuring that the battery pack stays within an acceptable range during its operation, regardless of the environmental conditions. Thus, to get a comprehensive estimate of the vehicle's true energy demand in a wide variety of environmental conditions, the project team created a model of a BTMS and implemented a simple control strategy. The heat rejection capabilities of the BTMS model are based on currently available BTMS systems.

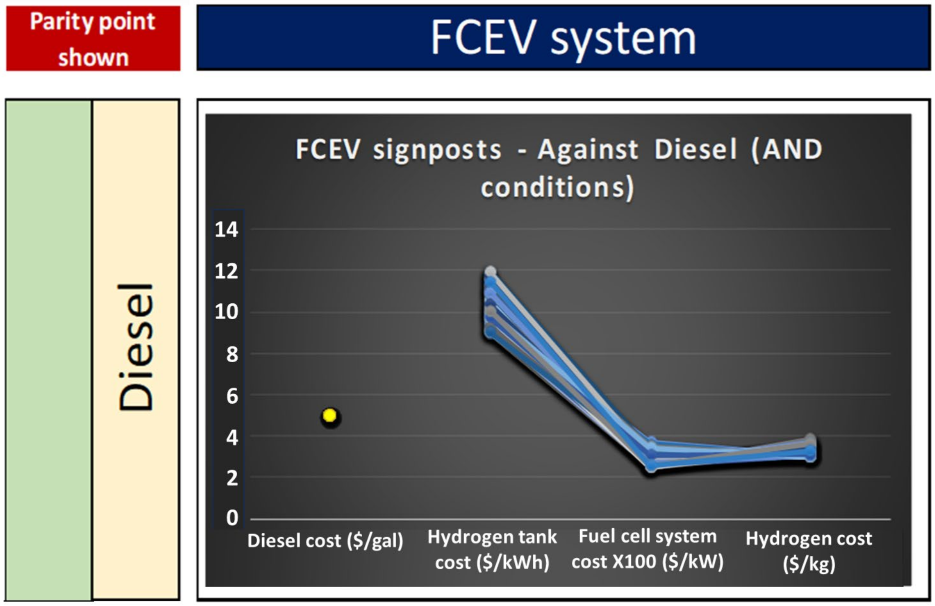
Charger Modeling

To better capture the dynamics of the plug-in charging process, the project team created models for single- and dual-plug chargers that have been integrated with the battery models discussed earlier. The plug-in charger models take two inputs that determine the maximum power that can be transferred from the charger to the battery: (1) an efficiency curve and (2) a charge acceptance curve. Additionally, the project team has created a model for an on-board dynamic wireless transfer charger. This charger model allows the vehicle model to accept power directly from a designated electrified segment of the vehicle's current route.

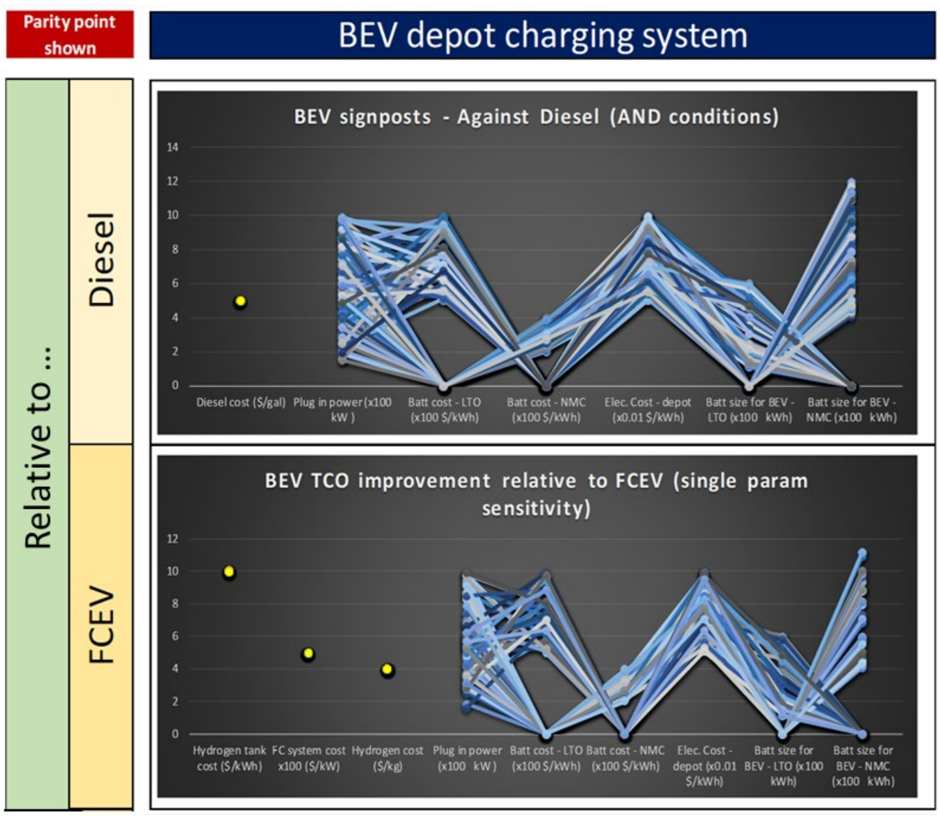
Vehicle Powertrain Options Analysis

Preliminary results using the above modeling (not accounting for the influence of weather) are seen for a fuel cell electric vehicle (FCEV) in Figure II.4.7, which presents a multi-factor assessment of the comparative architecture in relation to the reference architecture. Each setting or combination of factor values displayed here yields a TCO for the comparative architecture that outperforms the TCO of the reference architecture. This visual representation effectively illustrates the scenarios in which the comparative architecture exhibits cost advantages over the reference architecture, providing a comprehensive overview of the favorable configurations and conditions for decision-makers to consider. The factor values for the reference architecture are depicted as constants (seen as yellow points). For example, the price of diesel fuel is set at a fixed rate of $5 per gallon.

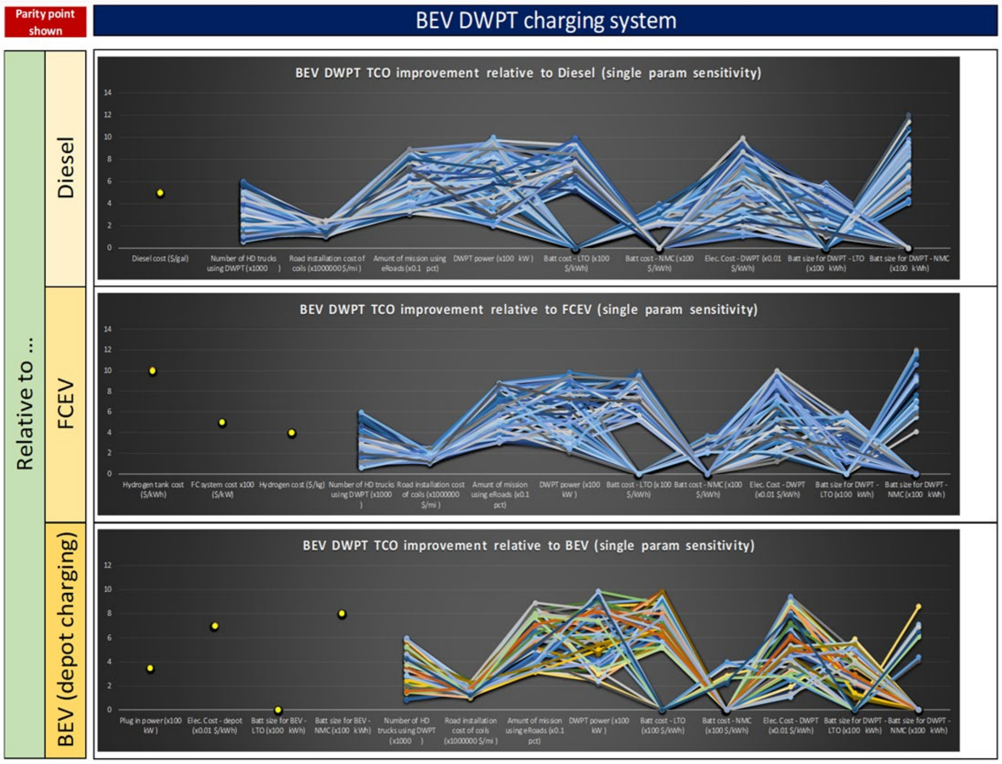
To achieve this view, the project team conducted a complex study that involves systematically varying critical parameter values and establishing the TCO/levelized cost of ownership of the different powertrain architectures. In all, the team studied over 47,000 configurations while considering a Monte Carlo space of 1,000 vehicles (varying missions and weights) for each configuration, i.e., 47,000,000 vehicle simulations. Using these data, the team generated a piecewise linear model to interpolate the TCO/levelized cost of ownership for other parameter settings. This has been done not only for the Drayage application but also for Line Haul, Regional Haul, and Short Haul in support of other U.S. Department of Energy (DOE) projects that need to understand these trade-offs. The outcomes from these critical signposts are incorporated into comprehensive route- and site-level analyses to evaluate the projected migration path of the architecture and the expected grid loading. In developing these roadmaps, anticipated cost and performance curves over time are employed, drawing from baseline scenarios [22] and exploring optimistic and pessimistic variations to establish the boundaries of the migration trajectories. Through constraint-based optimization, considering both TCO and Advanced Clean Fleet requirements, a migration trajectory for drayage routes is delineated.



(a)



(b)



(c)

Figure II.4.7 Multi-parameter TCO comparison of four systems: (a) diesel, (b) FCEV, and (c) BEV with depot and dynamic wireless power transfer (DWPT) charging. Source: ORNL

Future efforts will involve integrating this trajectory with a site-level evaluation of vehicles domiciled at the port, providing a more comprehensive characterization of the overall fleet migration pathway. However, because of factors such as fleet mission flexibility, uncertainty in the total vehicle count supporting drayage flow in a region, and constraints related to battery size (implications for weight), the results will offer guidance rather than specific targets for vehicle conversions.

To build out the above analysis into a site-level study, the project team has been developing an assessment of the anticipated vehicle count and weights that will be experienced by the Port of Savannah over the course of a typical year. For this study, we are focusing on 2021 data. In these studies, we develop a comprehensive perspective spanning 365 days, considering all trips to/from a single port. The objective is to assess the electric energy requirements based on a specific vehicle powertrain architecture. Using Monte Carlo statistical methods, vehicle counts originating from or destinating to the port, schedules of departure and arrival at the port, and weights for the Port of Savannah have been incorporated into vehicle missions. (These data are described above.) Missions are modeled as round trips that essentially emulate freight being transported from the port to a given destination, followed by an unloaded trip to a new origin point, where freight is reloaded and transferred back to the port. In this first pass, it is assumed that all mission energy for the trucks is obtained at the port. Truck battery sizes are limited to 1,000 kWh. These constraints limit the number of trucks that may be electrified without further charging opportunities, larger batteries, or alternate zero-emission powertrains. These options will be further evaluated in future BPs. Multiple charging scenarios have been considered using charger power levels of 150 kW, 350 kW, 440 kW, 1,250 kW, and 3,750 kW (covering both combined charging system direct current [DC] fast charging and megawatt charging system standards). In addition, four charging options have been considered: full recharge within the port dwell/service interval at or below the charger power limits, and full recharge within the port overnight dwell period at or below the charge power limits. Based on these possible charging solutions, the number of chargers needed, and the grid demand load may be calculated. Grid load demand for overnight charging of both at, and below, the charge power limits are shown in Figure II.4.8.

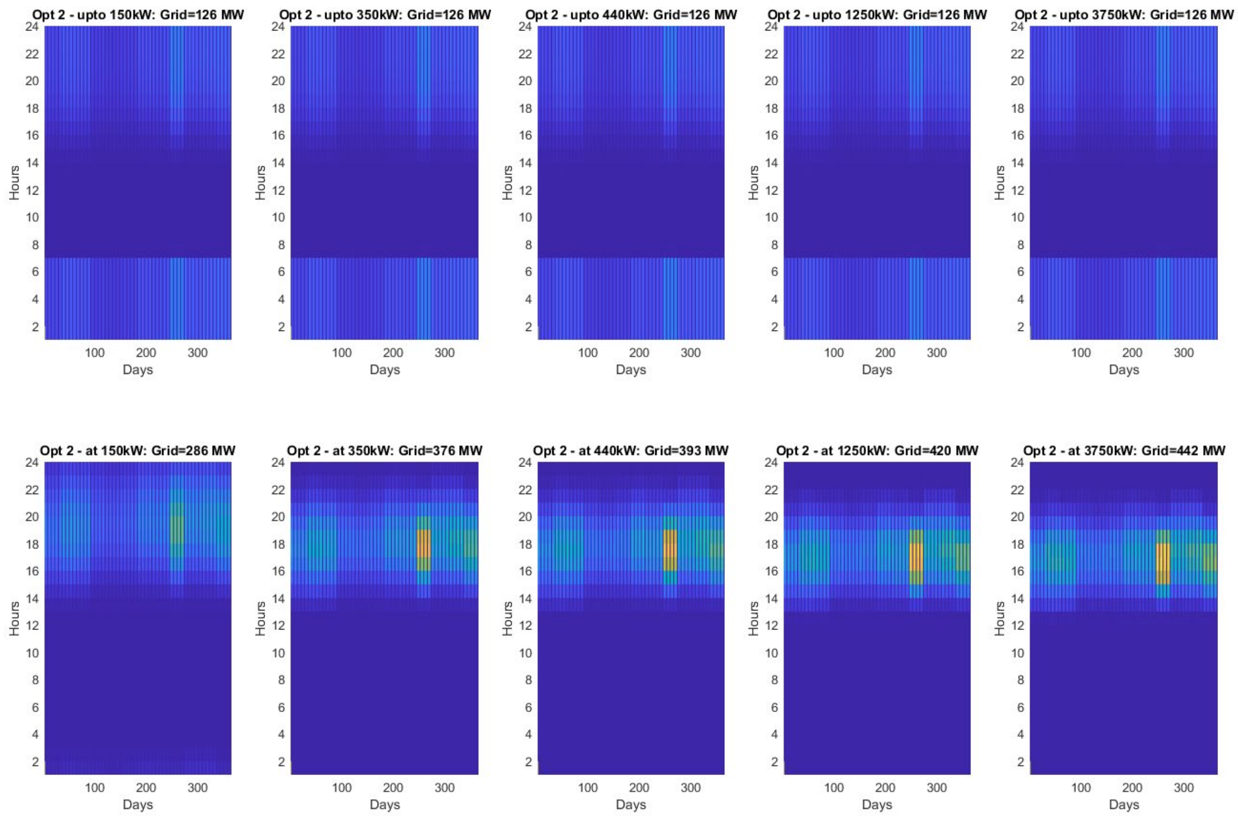
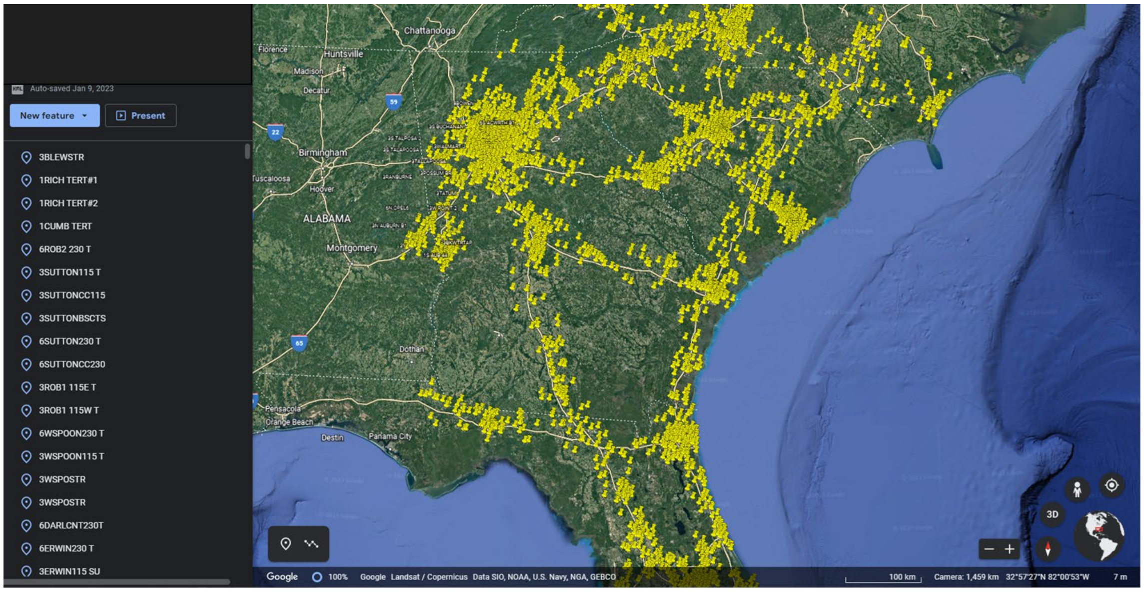


Figure II.4.8 Site-level truck throughput and grid power assessment. Source: ORNL

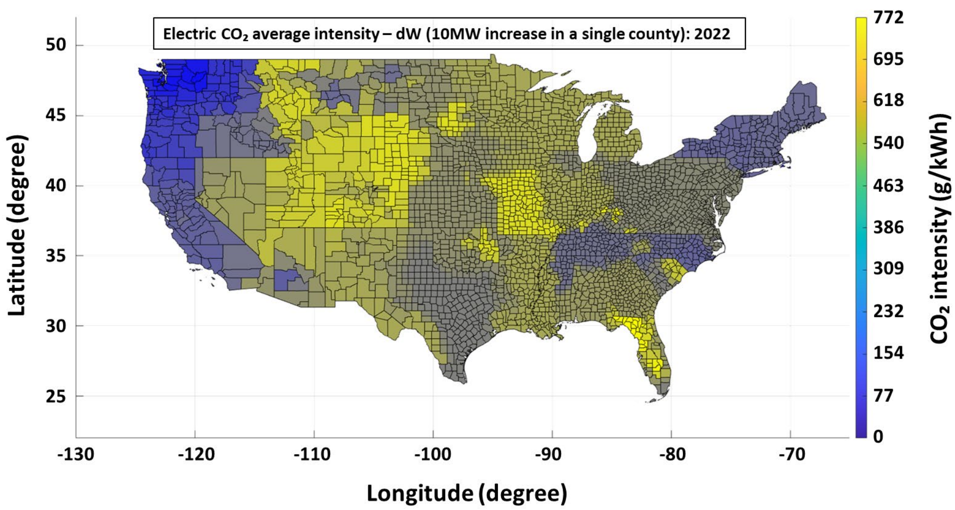
Like the assessment of vehicle architecture options, the team performed a similar assessment at the domicile level. This entails configuring the architecture for each energy solution, such as diesel and electricity (and hydrogen, natural gas, etc. in future projects), in a parametric manner. Key variations and associated range values are established, creating a study space for the infrastructure corresponding to a particular domicile. In addition to configuring the infrastructure, we can apply constraints—such as the availability of electricity or carbon emission limits—to determine the viability of a given infrastructure configuration. As with previous phases, the decision-making process predominantly centers around TCO. However, it may also incorporate other decision drivers aligned with the specific requirements and priorities of end-user stakeholders. The development of domicile-level studies will continue into the next two BPs, allowing us to delve deeper into the complexities of energy needs and infrastructure considerations at each major port in the United States.

Grid Capacity and DER Modeling

In parallel to the site-level energy demand, the team is conducting a study to assess the grid capabilities to support this demand. In a previous report, we have presented a direct assessment of capacity for substations within 250 miles of the Port of Savannah shown in Figure II.4.9(a)). These data reflect the limits that are experienced when a single electric bus at each substation experiences an increase in load till a failure mode is reached. Once we have the electric demand signal for the port, we will also explore the impact of multiple bus power increases to assess the ensuing failure modes.



(a)



(b)

Figure II.4.9 (a) **Assessing grid capacity near key roadways within 250 miles of the Port of Savannah, and** (b) **2022 grid carbon intensity estimation for additional load. Source: ORNL**

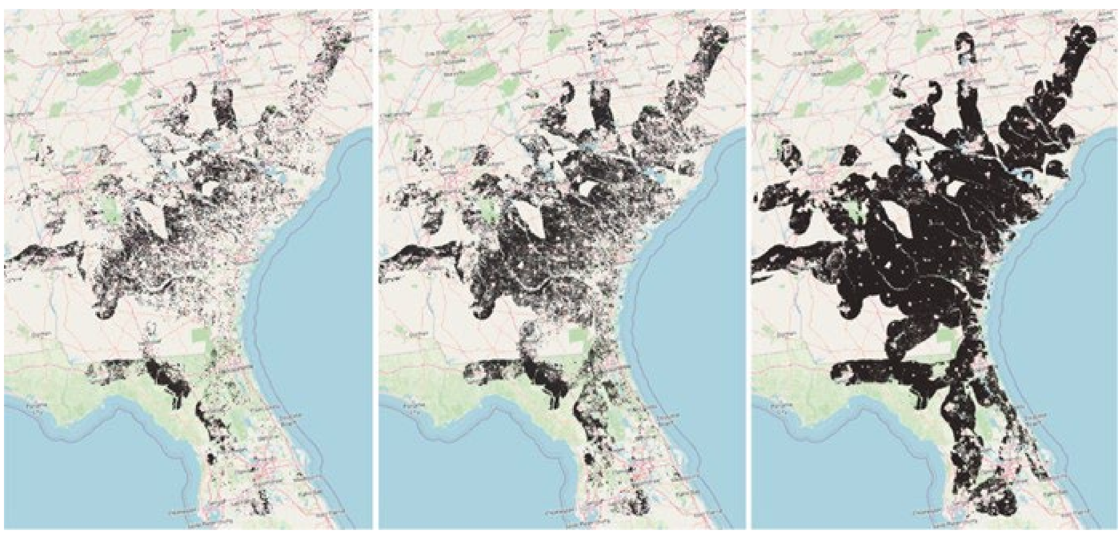
In addition to the grid capacity, it is critical to understand the grid carbon intensity associated with the additional load. Shifting the energy demand from traditional diesel or other fossil fuels to the electric grid does not eradicate the vehicle's carbon footprint; instead, it contributes to the overall carbon footprint originating from the grid. This stems from the reality that the grid is presently not carbon-neutral; it draws energy from various sources that generate carbon, including coal, natural gas, and oil. Even seemingly cleaner sources like nuclear, solar, wind, and hydroelectric power possess non-zero carbon intensities.

The team has introduced a novel tool that leverages historical data on the carbon intensity of the grid, specific to each electric zone, along with an estimate of the load demand in those zones. This tool forecasts the likely carbon intensity resulting from a new load within each region. The tool's purpose is to estimate the carbon intensity of an added load within any county in the United States, utilizing pertinent historical data and extrapolations derived from that data. The tool projects future carbon dioxide intensity by incorporating a grid decarbonization rate (user input to evaluate different hypotheses shown in Figure II.4.9(b).

Next, with knowledge of both the grid capacity and carbon intensity, the option of introducing DERs based on clean electricity (such as solar, wind, hydro, or nuclear) is explored. In future work, we will combine this asset class against the available electricity to identify the site-level options and their technoeconomic trade-offs.

To that end, we have modeled the DER siting challenges through previously developed laboratory tools funded by DOE, including both the National Renewable Energy Laboratory's (NREL) Renewable Energy Potential (reV) model and the ORNL Oak Ridge Siting Analysis for Power Generation Expansion (OR-SAGE) tool. Both are fundamentally DER siting tools but bring complementary functions to bear. OR-SAGE is specifically built for site selection and has the resolution to generate siting maps alongside regional data. OR-SAGE's unique approach to its exclusion layers allows in-depth analysis of the reasons behind a region's exclusion. NREL's rEV model is intended for regional and continental analysis rather than site selection. Both also bring into focus the needs for exclusion layers of the land.

Using the combination of both these tools, we have completed the analysis for solar siting requirements/ potential capabilities near the Port of Savannah, Houston, and Seattle–Tacoma shown in Figure II.4.10. Expanding the DER siting and TCO implication with wind, hydro, and nuclear will be considered going forward.



(a) (b) (c)

Figure II.4.10 Solar panel siting near Port of Savannah: (a) 10 MW sites, (b) 5 MW sites, and (c) 1 MW sites. Source: ORNL

Conclusions

The integration of BEVs into HD commercial freight transportation encounters substantial technoeconomic obstacles. To achieve widespread deployment of electrified powertrains in this sector, it is crucial to ensure high uptime and cost parity with diesel systems, all while adhering to safety regulations. However, challenges such as high powerplant and energy storage costs, elevated energy expenses, increased weight, extended refueling or recharging times, and limited supporting infrastructure have impeded the broad acceptance of BEV powertrains in HD freight transport.

In this research project, ORNL has developed an advanced CV road freight network, energy systems architecture, and a system-of-systems analytics framework called the OR-AGENT modeling framework. During BP 1, the primary focus has been developing and integrating the models and the OR-AGENT framework. This has been applied to the initial analysis of freight movement through the Port of Savannah using HD drayage trucks to co-assess the vehicle powertrain, the impact on the required charging infrastructure (at the ports), and the grid impact. BP 2 and BP 3 will expand on this by not only assessing a broader range of critical U.S. freight ports (including charging at the freight warehouses and along the roadways) but also developing a more in-depth assessment of the port infrastructure, coupled with the grid carbon impact, grid capacity gaps, and supporting DER asset deployment using deployment-critical TCO metrics.

Key Publications

1. Liu, Y., A. Siekmann, V. A. Sujan, M. Uddin, F. Xie, and S. Ou. 2022. "Providing levelized cost and waiting time inputs for HDV hydrogen refueling station planning: A case study of U.S. I-75 corridor." Proceedings of the 14th International Green Energy Conference (IGEC-XIV) 2022.
2. Lucero, J., V. A. Sujan, and S. Onori. 2023. "An experimentally validated electro-thermal EV battery pack model incorporating cycle-life aging and cell-to-cell heterogeneity." Submitted to the IEEE Transactions on Transportation Electrification. In revision.
3. Moore, A. M., A. Siekmann, and V. A. Sujan. 2023. "Spatio-temporal and weather characterization of road loads of electrified heavy duty commercial vehicles across U.S. Interstate roads." Proceedings of the 15th International Green Energy Conference (IGEC) 2023, July 10–13, Glasgow, UK
4. Siekmann, A., and V. A. Sujan. 2023. "Optimizing Long Term Hydrogen Fueling Infrastructure Plans on Freight Corridors for Heavy Duty Fuel Cell Electric Vehicles." 2024 SAE International Journal of Advances and Current Practices in Mobility 5(6), SAE World Congress 2023, Detroit, MI. DOI: 10.4271/2023-01-0064.
5. Siekmann, A., V. Sujan, F. Xie, Y. Liu, and M. Uddin. 2024. "Optimizing Hydrogen Fueling Infrastructure Plans on Freight Corridors for Heavy Duty Fuel Cell Electric Vehicles." SAE International Journal of Sustainable Transportation, Energy, Environment, & Policy 5(1). DOI:10.4271/13-05-01-0008.
6. Sujan, V. A., A. Siekmann, S. Tennille, and E. Tsybina. 2023. "Designing Dynamic Wireless Power Transfer Corridors for Heavy Duty Battery Electric Commercial Freight Vehicles." SAE Technical Paper 2023-01-0703, SAE World Congress 2023, Detroit, MI. DOI: 10.4271/2023-01-0703.
7. Sujan, V. A., and V. Galigekere. 2023. "Assessing Powertrain Technology Performance and Cost Signposts for Electrified Heavy Duty Commercial Freight Vehicles." SAE WCX™ (World Congress Experience) 2024, Detroit, MI.
8. Uddin, M., Y. Liu, F. Xie, V. A. Sujan, and A. Siekmann. 2022. "Modeling freight traffic demand and highway networks for hydrogen fueling station planning: A case study of U.S. Interstate 75 Corridor." Proceedings of the 14th International Green Energy Conference (IGEC-XIV) 2022.

References

1. U.S. Department of Transportation, Bureau of Transportation Studies. n.d. "Moving Goods in the United States." Accessed March 31, 2022. https://data.bts.gov/stories/s/Moving-Goods-in-the-United-States/bcyt-rqmu.
2. FleetOwner. 2020. "Trucking by the Numbers: A 2020 overview." December 28. https://www.fleetowner.com/operations/article/21150964/trucking-by-the-numbers-a-2020-overview.
3. Intermodal Association of North American (IANA). 2022. "Data & Statistics." https://www.intermodal.org/data-statistics/.

4. Truckstop. 2021. "Drayage Trucking: What It Is, Classifications, and Driver Shortages." https://truckstop.com/blog/drayage-trucking/.

5. Sujan, V. A., A. Siekmann, S. Tennille, and E. Tsybina. 2023. "Designing Dynamic Wireless Power Transfer Corridors for Heavy Duty Battery Electric Commercial Freight Vehicles." *2024 SAE International Journal of Advances and Current Practices in Mobility*, SAE World Congress 2023, Detroit, USA.

6. Sujan, V. A., and V. Galigekere. "Assessing Powertrain Technology Performance and Cost Signposts for Electrified Heavy Duty Commercial Freight Vehicles." Submitted to the 2024 SAE WCX, Detroit, MI.

7. U.S. Department of Transportation, Bureau of Transportation Studies. n.d. Based on 2019 data provided by the U.S. Army Corps of Engineers. Waterborne Commerce Statistics Center, special tabulation. Accessed November 2020.

8. StreetLight. n.d.. "Measure Transportation on the fly." Accessed June 10, 2023. https://www.streetlightdata.com/.

9. Nokia HERE. Accessed June 30, 2021. https://www.here.com/.

10. U.S. Census Bureau. n.d. "TIGER/Line® Shapefiles." Accessed July 7, 2021. http://www.census.gov/cgi-bin/geo/shapefiles.

11. Freight Analysis Framework (FAF), Data Tabulation Tool. Accessed July 12, 2021. https://faf.ornl.gov/faf5/dtt_total.aspx.

12. National Oceanic and Atmospheric Administration. n.d. "Meteorological Assimilation Data Ingest System." Accessed February 2023. https://madis.ncep.noaa.gov/index.shtml.

13. Moore, A. M., A. Siekmann, and V. A. Sujan. 2023. "Spatio-temporal and weather characterization of road loads of electrified heavy duty commercial vehicles across U.S. Interstate roads." *Proceedings of the 15th International Green Energy Conference* (IGEC) 2023, July 10–13, Glasgow, UK.

14. Shiledar, A., M. Villani, G. Rizzoni, E. Adinolfi, A. Pandolfi, A. Paolino, and C. Pianese. "A Modified Enhanced Driver Model for Heavy-Duty Vehicles with Safe Deceleration." *16th International Conference on Engines Vehicles*. SAE International, 2023. https://doi.org/10.4271/2023-24-0171.

15. Argonne National Laboratory. 2017. *Combined Aero and Underhood Thermal Analysis for Heavy Duty Trucks – Final CRADA Report*. ANL/NE-C1201001. https://publications.anl.gov/anlpubs/2017/02/133609.pdf.

16. Hyttinen, J., M. Ussner, R. Österlöf, J. Jerrelind, and L. Drugge. 2023. "Truck tyre transient rolling resistance and temperature at varying vehicle velocities – Measurements and simulations." *Polymer Testing* 122, 108004.

17. Gao, Z., C. Finney, C. Daw, T. LaClair, and D. Smith. 2014. "Comparative Study of Hybrid Powertrains on Fuel Saving, Emissions, and Component Energy Loss in HD Trucks." *SAE International Journal of Commercial Vehicles* 7(2).

18. Li, K., S. Luo, L. Fan, S. Hu, X. Zhou, R. Tu, H. Zhang, X. Jin, X. Zhao, and L. Su. 2021. "Investigation on the performance and characteristics of a heat pump system for electric vehicles

under extreme temperature conditions." *Case Studies in Thermal Engineering* 27, 101308, ISSN 2214-157X.

19. Ha, S., G. Pozzato, and S. Onori. 2023. "Electrochemical Techniques and Diagnostics for Lithium-ion Batteries." *Journal of Solid State Electrochemistry*.

20. Tanim, T., M. Shirk, R. Bewley, E. Dufek, and B. Liaw. 2018. "Fast charge implications: Pack and cell analysis and comparison." *Journal of Power Sources* 381" 56–65.

21. Lucero, J., V. Sujan, and S. Onori. n.d. "An experimentally validated electro-thermal EV battery pack model incorporating cycle-life aging and cell-to-cell variations." Submitted to the *IEEE Transactions on Transportation Electrification*. In revision.

22. Xie, Y., H. Basma, and F. Rodriguez. 2023. "Purchase costs of zero-emissions trucks in the United States to meet future Phase 3 GHG standards." Working paper 2023-10, International Council on Clear Transportation.

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II.5 Medium- and Heavy-Duty Electric Vehicle Load, Operations, and Deployment (HEVI-LOAD) Augmentation for National-Scale Infrastructure Assessment (Lawrence Berkeley National Laboratory)

Bin Wang, Co-Principal Investigator
Lawrence Berkeley National Laboratory
1 Cyclotron Rd.
Berkeley, CA 94720
E-mail: WangBin@lbl.gov

Wanshi Hong, Co-Principal Investigator
Lawrence Berkeley National Laboratory
1 Cyclotron Rd.
Berkeley, CA 94720
E-mail: WanshiHong@lbl.gov

Patrick Walsh, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Patrick.Walsh@ee.doe.gov

Start Date: October 1, 2022 End Date: September 30, 2024
Project Funding (FY23): $481,849 DOE share: $481,849 Non-DOE share: $0

Project Introduction

The global transportation sector plays a pivotal role in shaping the world's economy, with freight transportation serving as a vital component. Nevertheless, the environmental ramifications of traditional freight transportation fueled by fossil fuels have become increasingly alarming, prompting a collective effort to reduce greenhouse gas emissions and transition to more sustainable transportation modes. In this context, the electrification of freight transport has emerged as a critical strategy for achieving zero-emission freight transportation. The electrification of medium- and heavy-duty (MHD) vehicles presents a promising solution to address the environmental challenges. Replacing diesel-powered trucks with battery electric vehicles (BEVs) and fuel cell electric vehicles has substantial potential to significantly reduce carbon dioxide emissions, air pollution, and noise levels. Notably, advancements in powertrain technologies have enhanced the range and payload capacity of MHD zero-emission vehicles (ZEVs), rendering them viable options for long-haul and high-load transportation [1], [2].

While global initiatives and research endeavors have sought to promote freight electrification and zero-emission initiatives, challenges persist in achieving widespread adoption. Governments, private companies, and research institutions have recognized the urgency of zero-emission freight transportation and have implemented various policies and programs to support this shift, as discussed in [3] and [4]. Investigations into the influence of financial incentives and socioeconomic factors on electric vehicle (EV) adoption, underscore the need for coordinated efforts to facilitate the widespread adoption of MHD ZEVs. Despite the progress that has been made, challenges remain, including high upfront costs, limited charging infrastructure, range limitations, and concerns over battery life and performance [5], [6].

Objectives

This work aims to augment the ongoing research and development efforts in heavy-duty vehicle electrification by explicitly addressing the challenges of load deployment and charger assignment. In response, this project has developed the Medium and Heavy-Duty Electric Vehicle Infrastructure Load Operations and Deployment (HEVI-LOAD) tool. This tool serves as a comprehensive solution to project infrastructure needs for decarbonizing the MHD vehicle segments, offering valuable insights into optimizing charger assignments and ensuring the efficient operation of zero-emission MHD vehicles. In light of the existing challenges, this research aims to contribute to this evolving discourse by introducing an agent-based simulation method that resolves the intraday vehicle activities—driving, parking, and charging behaviors, etc.—with unprecedented temporal and geospatial granularities. This methodology addresses the existing gaps in modeling capabilities. It offers a tangible means to illustrate and demonstrate potential scenarios to key stakeholders and policymakers, facilitating more informed decision-making for a zero-emission future of freight transportation.

Specifically, in Fiscal Year 2023, the project team sought to forecast nationwide freight demand, leveraging existing datasets/models and identifying strategic locations (ports, truck stops, rest areas, etc.) for battery charging and hydrogen refueling infrastructure deployments along major highways. The subsequent objective was to process MHD trip volumes, freight road networks, and regional adoption scenarios as inputs to HEVI-LOAD. In addition, researchers planned to validate and calibrate the agent-based bottom-up simulations within HEVI-LOAD to provide comprehensive infrastructure analysis for MHD ZEVs at the national scale.

Approach

The HEVI-LOAD framework employs an agent-based simulation methodology. This approach models the trips and duty cycles of MHD ZEVs and generates charging load profiles and infrastructure assessment with varied resolutions: at the site (location), county, state, freight corridor, and national scales. The framework projects infrastructure deployment and operational needs, including charging/refueling station type, quantity, and strategic locations for future ZEVs weighing over 10,000 lbs. The HEVI-LOAD workflow is visually summarized in Figure II.5.1. The HEVI-LOAD analysis workflow consists of three major steps:

1. Data pre-process and scenario generation. The tool takes input data for travel demand, charger candidate locations, and road networks to create simulation scenarios.

2. Agent-based simulation. A detailed simulation is executed using pre-processed input data, accounting for adopted MHD ZEV trips, charging location details, and road network information, thus emulating real-world MHD ZEV driving, parking, and charging behaviors for a specified analysis region.

3. Results post-analysis. The tool summarizes event-based output data and provides energy demand analysis and infrastructure assessment.

Recently, smart charging management capacity was added, with heuristics and optimization methods to reduce peak load and flatten the load profile.

In particular, the freight road network utilized in HEVI-LOAD was extracted from the Freight Analysis Framework, and about 1,900 candidate truck stop locations were extracted from the Jason's Law Database [7] to be selected by the simulated trips as the public en route charging locations. The example national MHD travel demand model is illustrated in Figure II.5.2. Detailed assumptions and simulation methodologies will be discussed in a future report/paper. Because of space limitation in this report, the methodology focuses more on the overall analysis workflow and the preliminary results for BEVs.

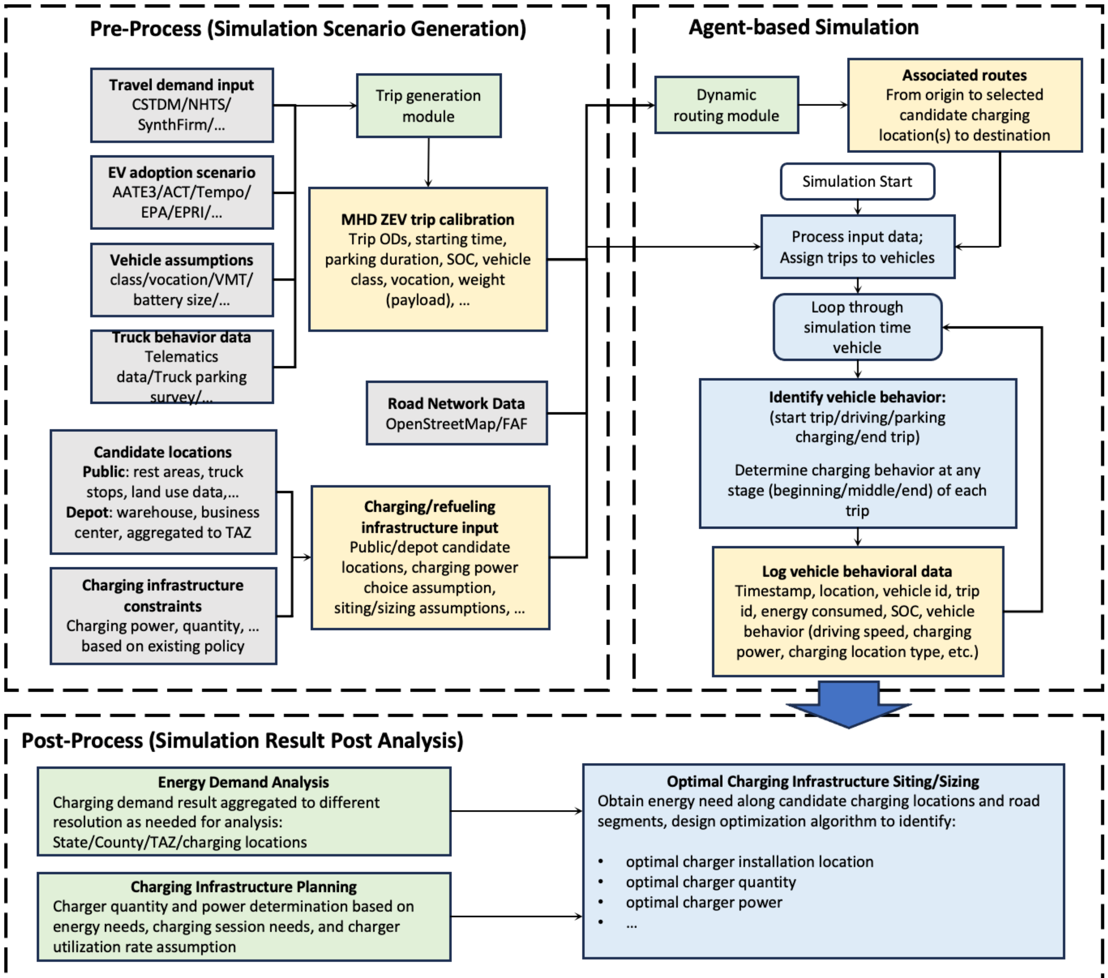
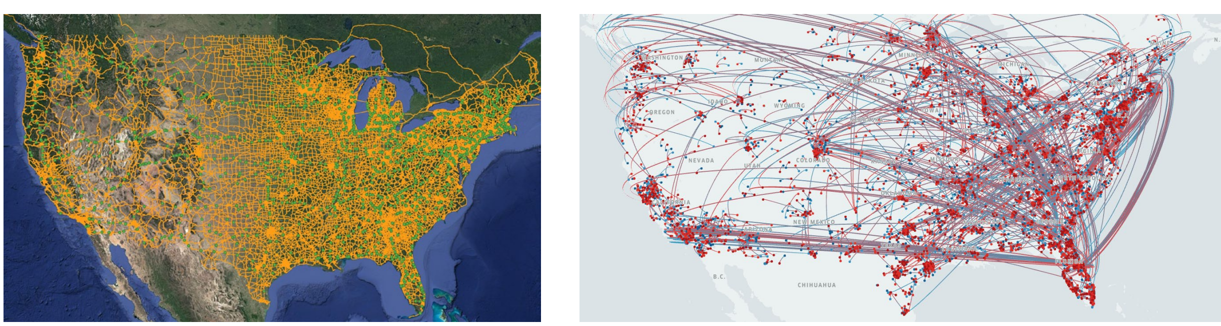


Figure II.5.1 HEVI-LOAD tool flow chart. Gray boxes are data inputs, green and blue boxes are methodology modules, and yellow boxes are output data from HEVI-LOAD. Source: Lawrence Berkeley National Laboratory (LBNL)



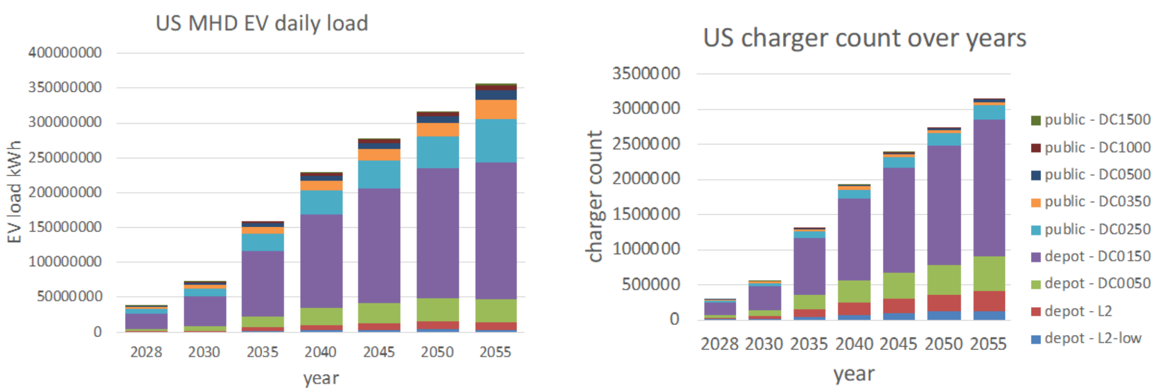
(a) **(b)**

Figure II.5.2 (a) Road network for MHD ZEVs extracted from the Freight Analysis Framework in yellow and the truck stop data from Jason's Law Database in green; (b) example travel demand model of MHD ZEVs at the national scale. Source: LBNL

Results

National Charging Demand and Load Analysis

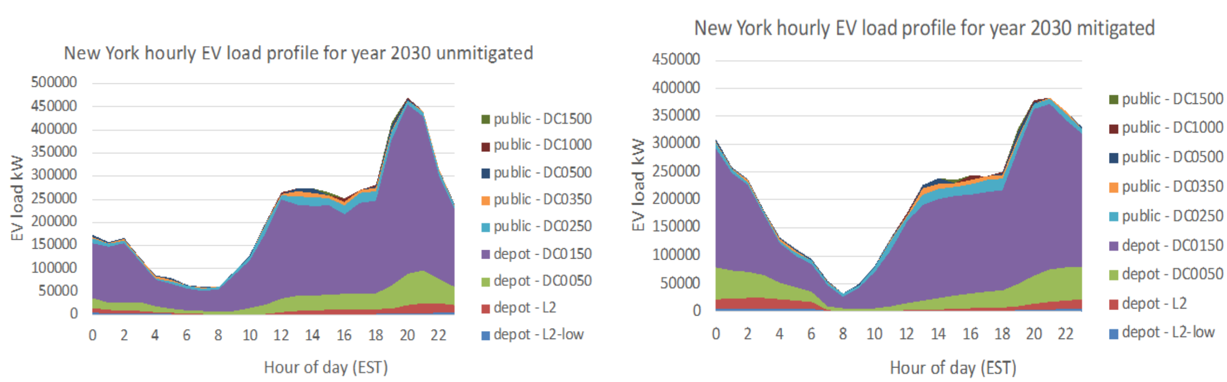
Based on the agent-based results, the HEVI-LOAD tool can aggregate the charging power and energy by each timestamp to different geospatial scales, such as site/location, county, and state levels. These energy demand results can be used to perform further charging infrastructure planning and circuit capacity analysis. Figure II.5.3(a) shows the overall EV daily load increment as the MHD ZEV population increases by years and Figure II.5.3(b) shows the increase in chargers over the same time frame. One can observe that the daily electricity usage by MHD EVs and the number of chargers will increase about ten times from 2028 to 2055.



(a) (b)

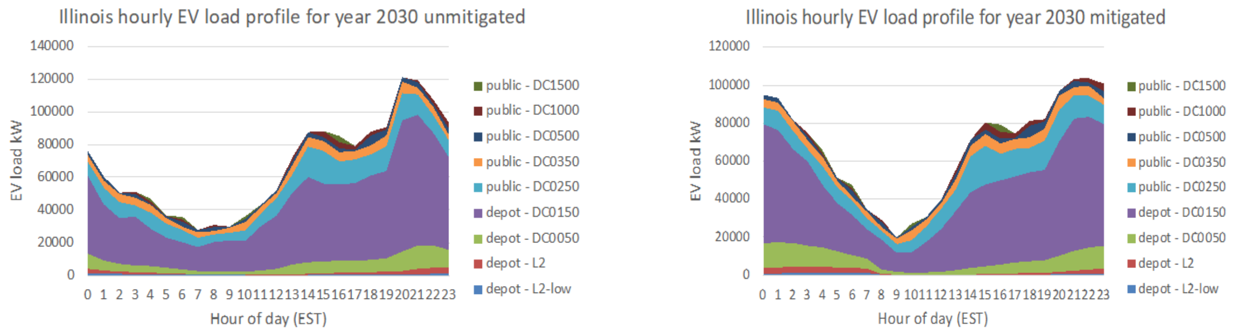
Figure II.5.3 (a) Daily energy demand by MHD ZEVs; (b) charging infrastructure needs at the national level. Source: LBNL

Figure II.5.4 and Figure II.5.5 show the hourly MHD EV load profiles for the states of New York and Illinois, respectively. In both cases, Figure II.5.4(a) and Figure II.5.5(a) show the unmitigated load, in which each vehicle follows the naturalistic charging behaviors, i.e., come-and-charge mode. Figure II.5.4(b) and Figure II.5.5(b) show the mitigated load, in which we assume the depot charging sessions can be managed, thereby reducing the energy used during peak energy demand hours. The peak EV charging load is reduced by 15%–16% for each state.



(a) (b)

Figure II.5.4 2030 New York State MHD EV hourly load profile, unmitigated (a) and mitigated (b). Source: LBNL



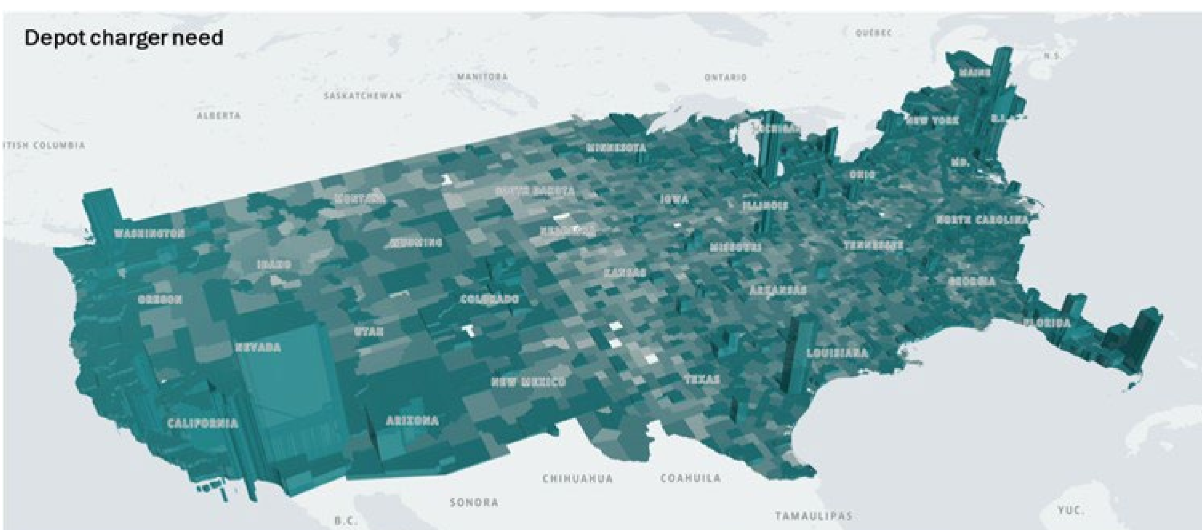
(a) **(b)**

Figure II.5.5 2030 Illinois State MHD EV hourly load profile, unmitigated (a) and mitigated (b). Source: LBNL

Charging Infrastructure Planning

Based on the energy demand results and the charging sessions obtained from the agent-based simulation, the HEVI-LOAD tool is able to provide a charging/refueling infrastructure assessment by determining the optimal type, quantity, and locations of charging/refueling stations. The project team projected the depot charger quantity/type by defining a fixed utilization rate for the charging sessions of different power levels at each analysis zone. An optimization siting/sizing algorithm was developed to determine the optimal public charger placement among all candidate locations that complete the charging requirements at a minimum combined cost of infrastructure installation and vehicle wait time. As shown above in Figure II.5.3(b), the charging infrastructure needs increase over the years; They are projected to increase nearly tenfold from 2028 to 2055. However, compared with the ZEV load increment in Figure II.5.3(a), the increment of charger counts trends toward saturation as 2055 draws near, due to the increase in potential infrastructure-sharing and utilization rate of each charger.

Figure II.5.6(a) shows the aggregated county-level charger needs for depot charging. Several U.S. metropolitan areas (e.g., Los Angeles, the San Francisco Bay Area, Chicago, and New York) represent highlighted depot charger demand, and one can observe in Figure II.5.6(b) that the public en route charger needs align well with the major freight corridors or port locations. This correlation is due to the assumption that these locations will have a high chance to be selected for MHD trips as en route charging locations.

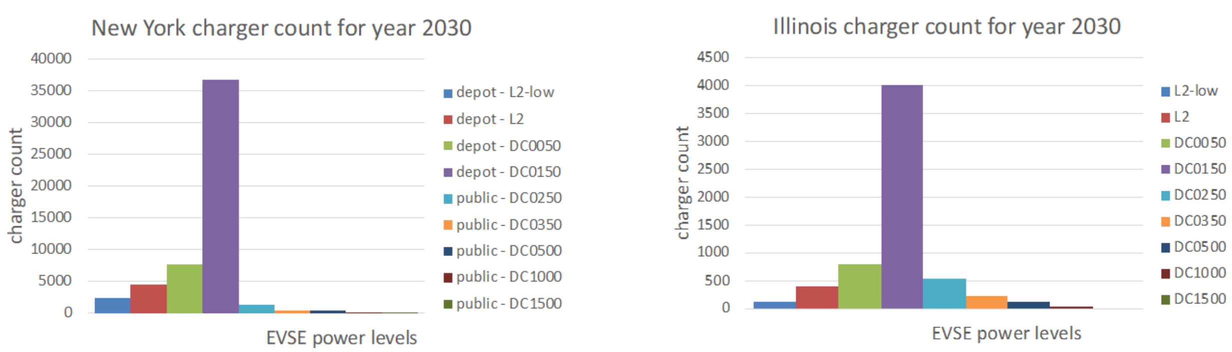


(a)

(b)

Figure II.5.6 Geospatial distribution of charging infrastructure needs. (a) Depot charger needs aggregated at the county level and (b) public en route charger needs aggregated at the county level. Source: LBNL

Figure II.5.7(a) provides the state-level charger count for New York and Figure II.5.7(b) for Illinois, which show that the public direct current 150 kW (DC0150) depot chargers account for the maximum depot charger needs because of charger choice and the economy of scale assumptions. The charger needs for public en route chargers are expected to be significantly lower in quantity than depot chargers, as it is characteristic for public chargers to serve more "just-in-time" charging needs with higher charging power levels.



(a) (b)

Figure II.5.7 State-level charger counts for (a) New York state and (b) Illinois. Source: LBNL

Conclusions

By leveraging agent-based simulation methodologies, the project team has augmented the capability of a valuable planning and operation tool for researchers, policymakers, and many other stakeholders, enabling informed decision-making in the pursuit of a sustainable and electrified future for freight transportation. Based on simulation results, the researchers could analyze the charging load and charger need increment trend for future years, specifically for MHD BEVs. The team further analyzed the influence of different charging behaviors on peak load and provided results for the hydrogen refueling infrastructure needs of MHD ZEVs. Moving forward, the integration of agent-based simulations in the discourse surrounding heavy-duty vehicle electrification holds promise for shaping effective policies and practices, propelling the freight industry toward a greener and more sustainable future.

Key Publications

1. Hong, W., and B. Wang. 2023. "Medium and Heavy-Duty Electric Vehicle Infrastructure: Load Operation and Deployment (HEVI-LOAD) – Methodology Overview," In preparation.

2. LBNL. 2023. "Medium and Heavy-Duty Electric Vehicle Infrastructure – Load Operations and Deployment (HEVI-LOAD) v2.0." Software copyright disclosure.

References

1. Greenblatt, J. B., and S. Shaheen. 2015. "Automated Vehicles, On-Demand Mobility, and Environmental Impacts." *Current Sustainable/Renewable Energy Reports* 2 (September): 74–81.

2. Fulton, L. M. 2018. "Three Revolutions in Urban Passenger Travel." *Joule* 2 (April): 575–578.

3. Klier, T., and J. Linn. 2018. "The road to zero-emission freight transport: From global solutions to local policies." *Transportation Research Part D: Transport and Environment* 61: 300–312.

4. Brand, C., J. Anable, and M. Tran. 2018. "Accelerating the electrification of urban freight vehicles: Identifying the challenges and opportunities for public policy." *Energy Policy* 117: 184–194.

5. Green, E. H., S. J. Skerlos, and J. J. Winebrake. 2014. "Increasing electric vehicle policy efficiency and effectiveness by reducing mainstream market bias." *Energy Policy* 65 (February): 562–566.

6. Forrest, K., M. Mac Kinnon, B. Tarroja, and S. Samuelsen. 2020. "Estimating the technical feasibility of fuel cell and battery electric vehicles for the medium and heavy duty sectors in California." *Applied Energy* 276 (October), 115439.

7. Federal Highway Administration (FHWA), 2020, "Jason's Law Truck Parking Survey Results and Comparative Analysis." https://ops.fhwa.dot.gov/freight/infrastructure/truck_parking/jasons_law/truckparkingsurvey/ch1.htm

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II.6 Managing Increased Electric Vehicle Shares on Decarbonized Bulk Power Systems (National Renewable Energy Laboratory)

Brennan Borlaug, Principal Investigator
National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
E-mail: Brennan.Borlaug@nrel.gov

Elaine Hale, Principal Investigator
National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
E-mail: Elaine.Hale@nrel.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: November 1, 2022	End Date: September 30, 2025	
Project Funding (FY23): $500,000	DOE share: $500,000	Non-DOE share: $0
Total Project Funding: $1,300,000	DOE share: $1,300,000	Non-DOE share: $0

Project Introduction

The accelerating shift toward plug-in electric vehicles (EVs) will have marked implications for the architecture and operation of future U.S. power systems [1]. Transportation electrification will be a key driver of electric grid expansion in the coming decades, and the specific patterns of EV charging (i.e., when and where EVs charge) will determine, in part, how this unfolds [2], [3]. At the bulk power level, EVs require additional electricity supply, which may necessitate the expansion of generation and transmission capacity. Planning for these shifts prompts the following questions: Will the demand patterns from EV charging complement the availability of low-marginal-cost renewable generation? Will they contribute to peak load pressures, necessitating additional generation capacity? To what extent can EV demands be scheduled or modulated, while preserving travel requirements, to enhance grid operations?

This project leverages and extends the National Renewable Energy Laboratory's (NREL's) transportation and power sector modeling capabilities to address multiple barriers associated with integrating high levels of plug-in EV charging into a decarbonizing bulk power system. Specifically, the analysis framework developed for this study simulates the evolution of the U.S. bulk power system through 2050 to accommodate large-scale EV charging across all on-road vehicle segments. The framework assesses the opportunities and value of demand-side flexibility (i.e., EV managed charging [EVMC], or "smart" charging) for reducing energy costs, increasing renewable penetration, and managing future EV loads on the bulk power system. The study also explores how the buildout of EV infrastructure can impact demand-side flexibility. This project will provide an improved understanding of anticipated challenges and least-cost solutions for managing load growth from EVs on the bulk power system. Additionally, EV load data sets for both unmanaged and managed charging scenarios will be made publicly available, with key findings summarized in a series of reports and publications.

Objectives

The objectives of this project are as follows:

1. Create and publish high-resolution data sets describing EV adoption and use, charging infrastructure, EV load profiles, and demand flexibility.

2. Publish high-impact analysis describing possible EV-grid futures and their costs and benefits with and without EVMC.

3. Extend modeling capabilities to be leveraged in future work and made available via open-sourcing and/or interface development as time, funding, and U.S. Department of Energy (DOE) priorities allow.

4. Ensure that the three objectives above are enriched by diverse input from the project's technical advisory committee (TAC), project team, and explicit outreach to various stakeholders through TAC connections and complementary DOE programs.

In the first year of this study (November 2022–September 2023), the focus was to convene a TAC, establish a scenario-based project framework, enhance existing transportation modeling capabilities, and initiate scoping of new grid modeling capabilities for development in Year 2 of the study.

Approach

An integrated framework connects NREL's transportation demand models (Transportation Energy & Mobility Pathway Options [TEMPO] [4] and Electric Vehicle Infrastructure [EVI]-X [5]) to its Regional Energy Deployment System (ReEDS) capacity expansion model [6], turning transportation data into EV charging demand inputs for grid planning and analysis. This approach is depicted in Figure II.6.1 and detailed in subsequent subsections.

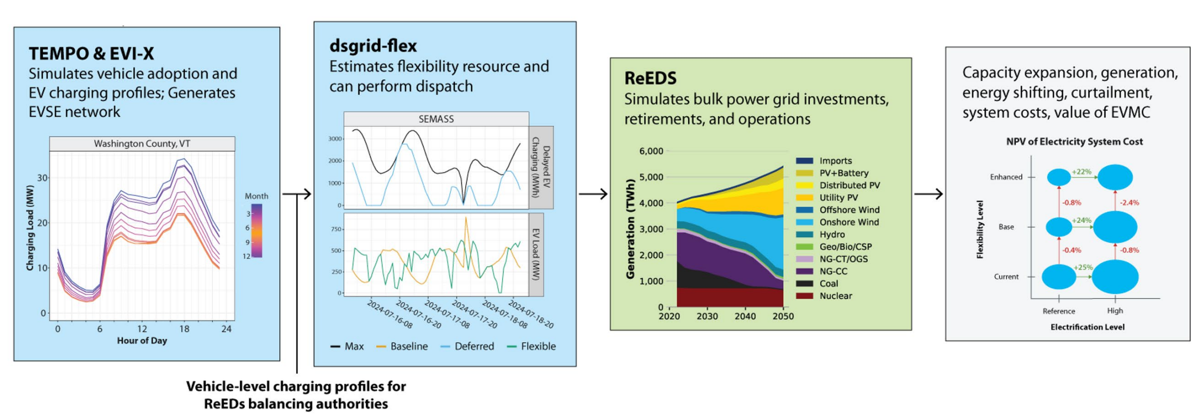

Figure II.6.1 Integrated analysis and valuation pipeline that models EV demands (TEMPO, EVI-Pro), parameterizes flexibility (design-side grid flexibility [dsgrid-flex]), and performs capacity expansion modeling (ReEDS) to estimate the costs and impacts of EVs as well as the value of EVMC for the bulk power system. Source: NREL

Transportation Modeling

This study leverages the TEMPO and the Electric Vehicle Infrastructure – Projection (EVI-Pro) models to perform high-resolution modeling of EV adoption, vehicle activity, charging demand, EV supply equipment (EVSE) access, and EV load profiles. TEMPO is a validated macro-model that generates long-term scenarios to meet strategic transportation–energy–environment objectives. It models the entire U.S. passenger and freight transportation sectors, simulating travel mode and technology adoption choices and projecting transportation energy use over time. For this study, TEMPO is used to develop multiple region-specific EV adoption trajectories for personal light-duty vehicles, freight and vocational medium- and heavy-duty vehicles (MHDVs), and buses (school and transit). Additionally, TEMPO produces vehicle-level models of charging flexibility, as described in Hale et al. [7], that can be aggregated into megawatt-scale, battery-like flexibility resources suitable for large-scale bulk power system models.

EVI-Pro is a tool for modeling EV charging behaviors and consumer demand for charging infrastructure based on detailed travel data, EV attributes, consumer charging preferences, and the availability and characteristics of EVSE at different location types. EVI-Pro has been used to assess EV charging network requirements and develop aggregate load profiles for numerous local, state, and national infrastructure analyses, including examples given in [8] and [9]. In this project, EVI-Pro is used to develop the baseline EV load profiles based on observed and modeled consumer charging behaviors, as well as to characterize the EVSE costs for enabling the various charging scenarios simulated in this study.

Grid Modeling

This study uses NREL's flagship ReEDS model to simulate the evolution of the U.S. bulk power system over time. ReEDS projects generator, transmission, and storage investments and retirements at a continental scale while capturing key operational characteristics of resources such as wind, solar, and storage. The model ensures reliability by co-optimizing planning reserves, operational reserves, and energy dispatch, outputting system costs, including capital costs for new resources, as well as fixed operations, maintenance, and operating costs for all resources, alongside emissions such as carbon dioxide and other greenhouse gases. ReEDS has been instrumental in numerous high-impact analyses for nearly two decades and has underpinned an annual Standard Scenarios report since 2015 [10].

The demand-side grid (dsgrid) model serves as the link between the transportation sector and power sector modeling in this project. It enables the transfer of basic EV load profiles from TEMPO and EVI-Pro into the ReEDS model. This project enhances the existing representation of EVMC within ReEDS by employing and refining dsgrid flexibility (dsgrid-flex) techniques to convert bounding vehicle-level charging profiles into aggregated grid-model-ready flexibility representations while inheriting all underlying travel constraints.

Project Scenario Framework

The project developed seven scenario concepts, considering varying assumptions around EV adoption, EV charging network design (i.e., EVSE access), how and where EVMC is implemented, and how the bulk power system could evolve in response to decarbonization objectives, non-transportation load forecasts, and the costs of competing technologies. These scenarios were developed from combinations of the *Decarbonization Futures* and *EV–Grid Integration Strategies* cases shown in Table II.6.1.

Table II.6.1 "Decarbonization Futures" and "EV-Grid Integration Strategies" Used to Construct Scenarios

Decarbonization Futures	Description
Low	Low ("business as usual") EV adoption paired with limited grid decarbonization
Mid	Mid ("accelerated") EV adoption paired with moderate grid decarbonization
High	High ("aggressive") EV adoption paired with rapid grid decarbonization
EV–Grid Integration Strategies	—
Baseline	Projected future EVSE access given current observed and stated EV charging preferences
Daytime	Increased daytime and reduced nighttime EVSE access
Flat	Increased daytime EVSE access and low-power EVSE prioritization
Flexible	Increased EVSE access at all location types and high-power EVSE prioritization, enabling maximum flexibility for active EVMC strategies
Stress	Increased home and MHDV depot high-power EVSE access, leading to an extreme afternoon-peaking load scenario, absent EVMC

The three *Decarbonization Futures* cases shown in Table II.6.1 describe how *Low*-, *Mid*-, and *High*-EV adoption could manifest within different vehicle segments (e.g., light duty vehicle, MHDV freight, buses), across regions (i.e., counties), and over time. Qualitatively, the *Low* ("business as usual") case corresponds roughly to currently enacted state and federal policies and continued government and industry investment in EVs and charging infrastructure. The *Mid* ("accelerated") case reflects moderately increased government and industry investment, as well as achievement of announced long-term (including non-binding) decarbonization targets. Finally, the *High* ("aggressive") case reflects aggressive investment in EVs and EVSE, achieving accelerated adoption in all vehicle segments and representing a scenario that meets or exceeds optimistic decarbonization targets. These EV adoption cases, developed with NREL's TEMPO model, will be coordinated across multiple DOE-supported efforts and subject to DOE, national lab, and industry review.

The five *EV–Grid Integration Strategies* cases shown in Table II.6.1 describe different charging network buildouts (i.e., varying EVSE access levels at different locations and port power capacities) and EVMC strategies (i.e., varying EVMC locations, dispatch mechanisms, and enablement costs). This project explores one *Baseline* strategy, three alternate management strategies (*Daytime*, *Flat*, and *Flexible*), and one "anti-management" strategy (*Stress*).

Results

In the first year of the study, the primary objectives were to convene a TAC, establish a scenario-based project framework, and enhance existing transportation modeling capabilities in preparation for large-scale EV travel and charging simulations in Year 2. Each of these activities is described in the following subsections.

Technical Advisory Committee

The team established an initial TAC in the first quarter of the project and held our first meeting on January 27, 2023. By the time of our second meeting, on September 29, 2023, the TAC had **20** members spanning Clean Cities participants (Dallas–Fort Worth Clean Cities, New Jersey Clean Cities, and Tennessee Clean Fuels); original equipment manufacturers (Ford and Daimler); EVSE and managed charging network providers (ChargePoint and FlexCharging); various power-sector stakeholders and service providers (PJM, National Grid, Camus Energy, and Pacific Gas & Electric Company); a state regulator (California Public Utilities Commission); and multiple researchers and consultants (Johns Hopkins University, Karlsruhe Institute of Technology, Atlas Public Policy, North Carolina Agricultural and Technical State University, Boston University, and Carnegie Mellon University). In the first meeting, the team gathered input from the TAC regarding the impact of EVs on the grid, the potential for EVMC, and general research topics worth exploring. This feedback guided the team's development of the project's scenario framework in the subsequent months. Similarly, after the project team provided an overview and received feedback on our transportation modeling approach, much of the second TAC meeting focused on soliciting thoughts, potential data sources, and other information that could be used to define reasonable EVMC supply curves in Year 2.

Project Scenario Framework

The seven scenario concepts developed for this study reflect pairings of *Decarbonization Futures* and *EV–Grid Integration Strategies* as seen in Figure II.6.2. First, *Low*-, *Mid*-, and *High-Baseline* scenarios serve as central comparative cases. *Mid*-, and *High-Baseline* scenarios contain both unmanaged (informed from historical charging activity data and simulated by NREL's EVI-Pro model) and managed charging scenarios; the *Low-Baseline* scenario will be simulated as unmanaged only. For each of the alternative (non-*Baseline*) *EV–Grid Integration Strategies*, the *High Decarbonization Futures* case is retained (*High-Daytime, High-Flat, High-Flexible, High-Stress*), as it is the most analytically interesting, and both unmanaged and managed scenarios are simulated. These scenarios provide a framework for analyzing how factors such as EV adoption, EVSE network design, and EVMC could impact the bulk power system.

Scenario Concepts

Scenario Dimension	Low-Baseline	Mid-Baseline	High-Baseline	High-Daytime	High-Flat	High-Flexible	High-Stress
Decarbonization Future	Low	Mid	High	High	High	High	High
EV-Grid Integration Strat.	Baseline	Baseline	Baseline	Daytime	Flat	Flexible	Stress
EVSE Access & Use	Baseline	Baseline	Baseline	High Work/Pub, Low Home	High Work/Pub, Low Power	High EVSE, High Power	High Home, High Power
EVMC Supply Curves		Mid-Flex	Mid-Flex	Mid-Flex	Flat	High-Flex	Low-Flex
Grid-Base (decarb; competing tech.)		Mid; Mid	100% by 2035; High-Batteries	100% by 2035; High-Batteries	100% by 2035; High-Batteries	100% by 2035; High-Batteries	100% by 2035; High-Batteries
Grid-Sensitivity 1 (decarb; competing tech.)			Mid; High-Batteries	100% by 2035; Low-Flex	100% by 2035; Low-Flex	100% by 2035; High-Tech	100% by 2035; Low-Flex
Grid-Sensitivity 2 (decarb; competing tech.)						100% by 2035; High-Complete	

Unmanaged profiles only

Central scenarios *Grid sensitivity enables waterfall charts of transport & power decarb. impacts*

Passive strategies *How far can we get with basic shaping strategies?*

Active strategy

Anti-strategy *What's the cost of convenience?*

Figure II.6.2 High-level scenario framework. Source: NREL

Transportation Modeling Enhancements

Enhancements to TEMPO and EVI-Pro were made in the first year of the project to enable MHDV charging simulations and represent location-specific variable EVSE access. EVI-Pro now supports week-long charging simulations to better capture within-week charging patterns and demand flexibility. These new features set the stage for developing the highly resolved EV load and flexibility profiles with national scope in Year 2 of the project.

A key investigation in this study is to explore how the design and buildout of the EVSE network might passively shape EV charging demand even without EVMC controls. The team leveraged over 150,000 daily vehicle travel profiles from the 2017 National Household Travel Survey [11] to model charging under different levels of EVSE access. Scenarios ranged from drivers having extensive charging options (i.e., home, workplace, and frequent public destination EVSE) to "charging deserts" restricted to high-speed en route (i.e., trip-interrupting) and limited public destination options. Figure II.6.3 illustrates the impact of EVSE access on the shape and locational mix of unmanaged EV charging demands: those with home chargers do most of their charging at home and overnight, whereas while those without home chargers charge more during the day, relying on high-power direct current fast chargers to satisfy their daily travel requirements. The en route direct current fast charger option, modeled as trip-interrupting and less inconvenient, is not seen as a flexible source of demand compared to destination-based charging options.

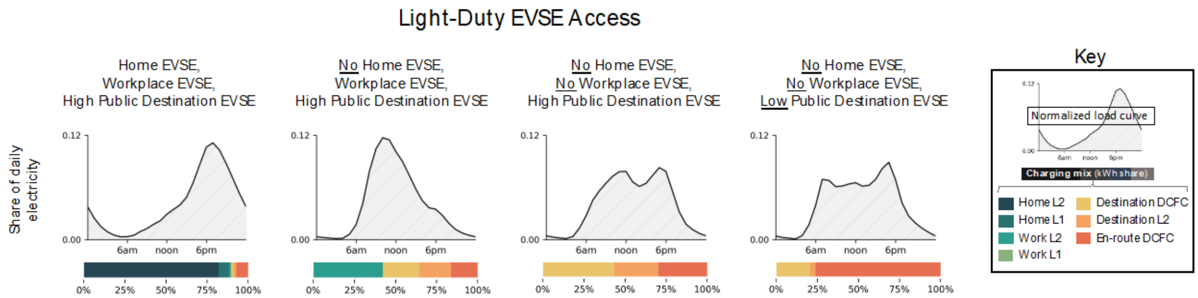

Figure II.6.3 Modeled impact of EVSE access (home, work, public) on EV load shapes and charging mix. Source: NREL

Conclusions

The first year of the "Managing Increased Electric Vehicle Shares on Decarbonized Bulk Power Systems" project has laid the groundwork to deliver on the project's ambition to develop unique, timely, and highly resolved data sets describing future EV charging loads for all on-road vehicle segments (i.e., light-, medium-, and heavy-duty), both unmanaged and managed. Additionally, an analysis was conducted that describes to what extent both passive (e.g., based on EVSE deployment options) and active management strategies could reduce the costs of integrating EVs into a simultaneously decarbonizing grid.

Specifically, in Year 1, the team:

- Established a TAC to guide the project and provide robust review of work products.
- Produced a comprehensive scenario framework that provides the entire team, transportation and grid, with a roadmap for which data sets and modeling capabilities to develop.
- Developed most of the transportation modeling methodology and input datasets.
- Began gathering the data and insights needed to construct the EVMC supply curves that will guide our power sector capacity expansion model's economically efficient selection of EVMC quantities (number of participating vehicles, informed by participation rates as a function of incentive level) and types (e.g., direct load control or price-responsive).

For the next year, we look forward to having created and published all the transportation scenario data to be delivered as part of this project. We also anticipate having the grid modeling methods and near-complete data assembled and ready for conducting this project's capstone analysis.

References

1. Muratori, Matteo, Marcus Alexander, Doug Arent, Morgan Bazilian, Pierpaolo Cazzola, Ercan Dede, John Farrell, Chris Gearhart, David Greene, and Alan Jenn. 2021. "The Rise of Electric Vehicles – 2020 Status and Future Expectations." *Progress in Energy* 3(2): 022002. DOI 10.1088/2516-1083/abe0ad.

2. Mai, Trieu, Paige Jadun, Jeffrey Logan, Colin McMillan, Matteo Muratori, Daniel Steinberg, Laura Vimmerstedt, Ryan Jones, Benjamin Haley, and Brent Nelson. 2018. *Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States*. NREL/TP-6A20-71500. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy18osti/71500.pdf.

3. Muratori, Matteo and Trieu Mai. 2020. "The shape of electrified transportation." *Environmental Research Letters* 16(1): 011003. DOI 10.1088/1748-9326/abcb38.

4. NREL. n.d. "TEMPO: Transportation Energy & Mobility Pathway Options Model." Accessed 2023. https://www.nrel.gov/transportation/tempo-model.html.

5. NREL. n.d. "EVI-X Modeling Suite of Electric Vehicle Charging Infrastructure Analysis Tools." Accessed 2023. https://www.nrel.gov/transportation/evi-x.html.

6. NREL. n.d. "Regional Energy Deployment System." Accessed 2023. https://www.nrel.gov/analysis/reeds/.

7. Hale, Elaine, Luke Lavin, Arthur Yip, Brady Cowiestoll, Jiazi Zhang, Paige Jadun, and Matteo Muratori. 2022. *Electric Vehicle Managed Charging: Forward-Looking Estimates of Bulk Power System Value*. NREL/TP-6A40-83404. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy22osti/83404.pdf.

8. Wood, Eric, Brennan Borlaug, Matt Moniot, D-Y Lee, Yanbo Ge, Fan Yang, and Zhaocai Liu. 2023. *The 2030 National Charging Network: Estimating U.S. Light-Duty Demand for Electric Vehicle Charging Infrastructure*. NREL/TP-5400/85654. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy23osti/85654.pdf.

9. Alexander, Matt, Noel Crisostomo, Wendell Krell, Jeffrey Lu, and Raja Ramesh. 2021. *Assembly Bill 2127: Electric Vehicle Charging Infrastructure Assessment: Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030*. CEC-600-2021-001-CMR. Sacramento, CA: California Energy Commission. https://efiling.energy.ca.gov/getdocument.aspx?tn=238853.

10. Gagnon, Pieter, Maxwell Brown, Dan Steinberg, Patrick Brown, Sarah Awara, Vincent Carag, Stuart Cohen, Wesley Cole, Jonathan Ho, Sarah Inskeep, Nate Lee, Trieu Mai, Matthew Mowers, Caitlin Murphy, and Brian Sergi. 2022. *2022 Standard Scenarios Report: A U.S. Electricity Sector Outlook*. NREL/TP-6A40-84327. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy23osti/84327.pdf.

11. U.S. Department of Transportation, Federal Highway Administration. n.d. "National Household Travel Survey." Year selected: 2017. Accessed 2023. https://nhts.ornl.gov/.

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II.7 Assessing Opportunities for Travel Demand Management in the Context of Decarbonization and Equity (National Renewable Energy Laboratory)

Christopher Hoehne, Principal Investigator
National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
E-mail: Christopher.Hoehne@nrel.gov

Matteo Muratori, Principal Investigator
National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
E-mail: Matteo.Muratori@nrel.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

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Project Introduction

Achieving deep decarbonization of the transportation sector, currently the largest source of greenhouse gas (GHG) emissions, will require profound changes within multiple complex systems, including a transition away from petroleum fuels that today provide over 95% of transportation energy. Emissions can be reduced by limiting growth in mobility demand (i.e., traveling less), shifting to more energy efficient mobility modes where possible (e.g., taking public transit or walking, biking, or other mobility alternatives), including increased sharing of automobile trips where other modes aren't viable, and reducing the emissions associated with mobility (i.e., adopting energy efficiency measures and clean fuels). While technology solutions targeting efficiency and fuel replacement are generally understood and central to current decarbonization strategies, additional opportunities to reduce transportation emissions through improved system design and demand management are less clear. There is significant potential to capitalize on the rapid technological advancements and shifting paradigms of mobility needs caused, in part, by pandemic-induced behavioral changes and other socioeconomic trends. Mobility is rapidly evolving, and emerging trends (e.g., micromobility, desire to limit unnecessary travel, and multi-modal travel) and business models (e.g., mobility as a service) are having significant impacts on travel demand—although the impacts vary for different consumers. To add to this complexity, COVID-19 disrupted expected norms of travel patterns, highlighting how mobility needs can fundamentally change, particularly through the displacement of physical travel (e.g., telework). With new and rapidly evolving technology options shaping mobility needs, it is not clear how new mobility and economic paradigms (e.g., widespread telework) could impact emissions pathways toward deep decarbonization.

Recent studies highlight how travel demand management (TDM) strategies can lead to emissions reductions, but significant reductions to total travel demand will be difficult to realize, as travel has important economic and social benefits [1]. Additionally, different population segments will be non-uniformly affected by policies and mechanisms to manage travel demand, as their needs are heterogenous. As all pathways to deep decarbonization of mobility require major shifts to clean alternative fuels (mostly relying on clean electricity), taming future electricity demand by capitalizing on effective TDM solutions would help not only reduce emissions but also lessen pressure on power-sector expansion and manage grid-side demand [1], [2]. Despite recent research pointing to the need for managing travel and energy demand as the economy grows and increasingly electrifies [3], there is great uncertainty around how travel demand could evolve in response to changing mobility needs and emerging technologies, and how TDM strategies would impact different consumers. Furthermore, no known research has explored what magnitude and mechanisms will be feasible for managing travel demand at a national level, especially in the context of decarbonization to quantify emissions reduction opportunities of different actions and their equity impacts (i.e., how strategies to manage demand could affect the quality of travel for different socioeconomic groups).

A national-level perspective on the impact of demand-side management solutions to mitigate transportation emissions has been missing in the extended Vehicle Technologies Office portfolio of tools and analysis capabilities. Tools such as regionally calibrated agent-based models do not capture the entire nation, nor do they identify the tradeoffs between different regions and consumer types. Tools usually leveraged for long-term projections of benefits focus on technology replacement (e.g., replacing conventional vehicles with electric vehicles) and do not capture either the key mobility aspects driving travel demand or the uncertainty in demand as it evolves over time.

Objectives

The objectives of this project are to:

- Quantify the uncertainty around future travel demand, the key drivers of this uncertainty, and the impacts that these drivers could have on achieving deep decarbonization.
- Evaluate various technology advancements and policies aimed at better managing the growth of travel demand, especially along key dimensions of uncertainty, and identify key strategies that maintain the benefits of travel across subpopulations to support deep decarbonization. There is also potential for some strategies to synergize with other identified goals for addressing transportation decarbonization, such as accelerated zero-emission vehicle adoption or modal shifts.
- Quantify the benefits of different travel management solutions and their impacts on equity to inform policy and decisions around net-zero scenarios.

A key goal of this project is to understand the potential impacts across different socioeconomic groups and to ensure that there are equitable strategies for managing travel demand (including understanding any potential unintended consequences). Previous literature has identified household budgets as a key factor that can impact equitable mobility options. Relatedly, car ownership can make up a sizable portion of a household's budget, yet owning a personal car is often seen as necessary to compete for access to a wide variety of jobs and gain access to a higher number of activities that define a higher quality of life [4]. The project will focus on how different solutions to managing travel demand could adversely impact those with lower household incomes (and thus lower travel budgets), as well as households with few or no drivers. Additionally, trip purpose by socioeconomic status is a principal factor in understanding essential vs. non-essential travel across groups.

Approach

We leverage National Renewable Energy Laboratory's (NREL's) Transportation Energy & Mobility Pathway Options™ (TEMPO) model [5] to explore travel management solutions—including associated impacts and opportunities—to reduce U.S. transportation GHG emissions. TEMPO is a validated macro-model that produces long-term scenarios to reach strategic transportation–energy–environment objectives and assess synergies with energy supply [6]. TEMPO models the entire passenger and freight U.S. domestic transportation sector, simulating travel mode and technology adoption choices, and ultimately projects transportation energy use over time. TEMPO characterizes opportunities for existing and future fuels, technologies, and travel business models across national transportation sub-sectors and segments capturing mobility needs for different consumers (e.g., different income levels, urbanity, and access to alternative travel modes) and applications. Using TEMPO's unique household-based representation of personal travel, the project team will develop scenarios to:

- Capture uncertainty in the evolution of future travel demand, e.g., housing density shifts, changing availability and quality of transport modes (e.g., transit, micromobility), and demand for telework and virtual mobility.
- Represent and assess TDM strategies to incentivize more efficient and easier-to-manage travel behavior (travel time shift, voluntary reductions, etc.) to support equitable decarbonization.

The first task in this project focuses on conducting a comprehensive literature review on TDM strategies and developing a TDM inventory of data points to inform and validate future modeling in TEMPO. Next, preliminary scenarios will be designed to explore the TEMPO model's ability to represent key dimensions and outcomes in the TDM space. Scenario results from TEMPO modeling will be evaluated against literature, and necessary enhancements and calibration will be conducted to prepare for the final task. The final task will focus on developing a set of carefully designed scenarios across multiple TDM strategies to reveal their impacts on key TDM metrics (e.g., number of trips, emissions), their synergies with each other, and their impacts on various household types relevant for equitable mobility (e.g., no-vehicle households, low-income households). Final results will be summarized to inform how various TDM strategies can contribute to national-level efforts to support decarbonization across the United States.

Approach for Literature Review of Travel Demand Management Strategies

A comprehensive literature review was designed to gather data and trends across existing research on the impacts of TDM strategies on travel demand and mobility. The literature review focused on research articles with quantitative analysis estimating impacts of various TDM solutions across different metrics/spatial scales, and the spatial scope included research in the United States, as TEMPO is currently focused and calibrated to assess U.S. mobility. A systematic scan of scientific literature was performed using Google Scholar and Scopus (via an application programming interface), supplemented by shared research from colleagues. Leveraging the Scopus database with an automatic script and filtering mechanisms makes it easy to refresh the search to retrieve the most up-to-date literature periodically.

Preliminary Scenario Development

The literature review and TDM inventory development revealed that one of the most discussed topics is changes to urban development and land use. As a result, the first set of preliminary scenarios developed focused on this topic by examining how shifting household urbanities (densities) within TEMPO impact travel demand. The spectrum of test scenarios included extreme urbanization (high shifts toward urban/secondary-city households by 2050) to extreme decentralization (high shifts away from urban/secondary-city households by 2050), as well as a suburbanization scenario where housing shifts are concentrated more strongly in suburban housing densities. Figure II.7.1 shows the trajectory of housing shifts by TEMPO household classification for the two most extreme scenarios. In the Figure II.7.1(a), Extreme Urbanization, there is a large shift away from rural and small-town housing, with high growth in urban and secondary-city housing. In Figure II.7.1(b), Extreme Decentralization, the opposite occurs; there are large shifts toward rural and small-town housing and away from urban areas.

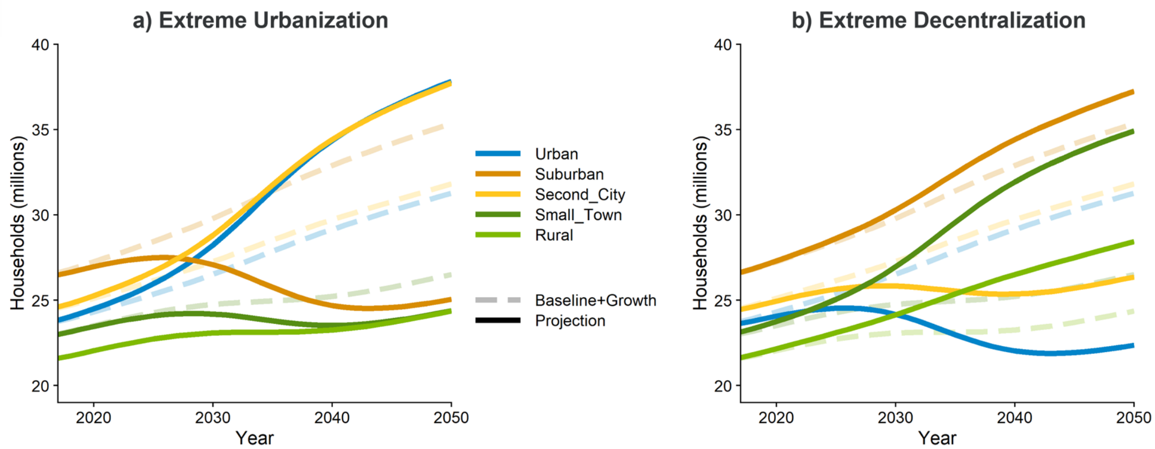

Figure II.7.1 Projected changes to TEMPO household urbanity classification for the two most extreme scenarios: (a) extreme urbanization and (b) extreme decentralization. Source: NREL

Results

Inventory Results from Literature Review of TDM

The project team analyzed the body of collected research, prioritizing more recent studies. Only studies that had quantitative results that could be extracted were inventoried into a data spreadsheet. This TDM inventory summarized the collected body of literature across key metrics (e.g., emissions, vehicle miles traveled [VMT]), outcomes, scope, methods, timescale, and other relevant aspects. Overall, 34 research studies conducted across numerous regions in North America were reviewed and inventoried. The project team recorded 159 data points in the TDM inventory, all related to the magnitude and relationships of various strategies to manage travel demand. The following are key findings from this TDM inventory:

- No current research is national in scope and forward-looking.
- Most research quantifying and discussing impacts of TDM were retrospective (i.e., historical analysis – 91%).
- Only three studies (9%) focused on future modeling of TDM impacts on the transportation system.
- Only a few studies (12%) assessed impacts at a national scope.
- Most research quantifying and discussing impacts of TDM uses statistical analyses or statistical modeling on historical data.

The first bullet is significant, as the TEMPO model is designed to be both national in scope and forward-looking and thereby can address this research gap. Figure II.7.2 shows a summary of the TDM impacts from the collected body of literature across three key metrics: emissions, trips, and VMT. Across these three metrics, impacts as a percentage change to the baseline/control were concentrated between a few percent to around -25%. A few outliers showed impacts could be very large if the focus is only on specific modes (e.g., transit-oriented development caused large increases in transit and walking trips in the study area).

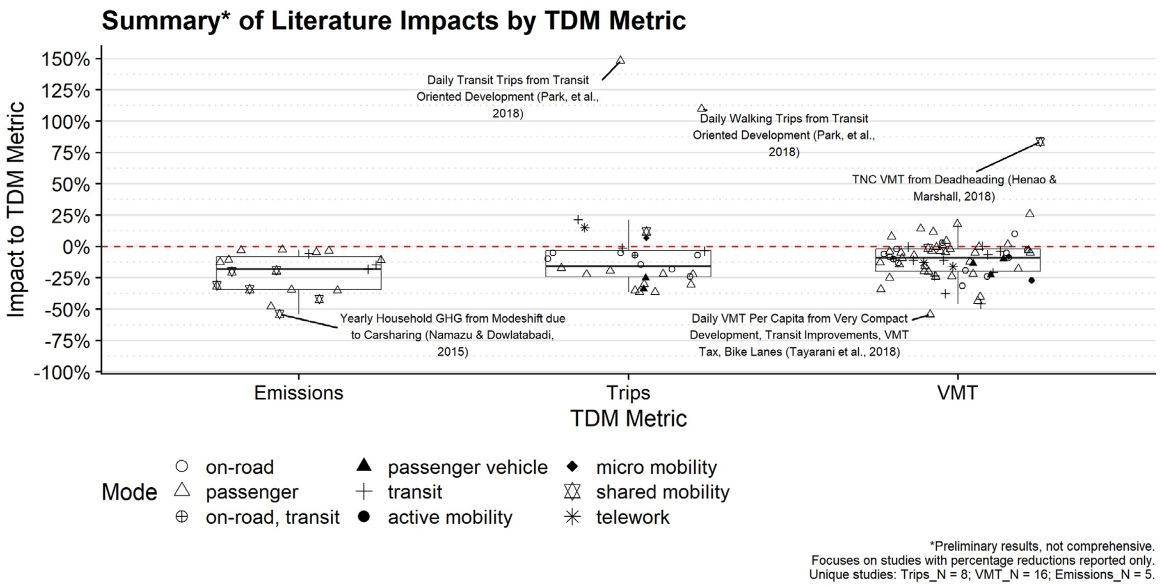

Figure II.7.2 Summary of TDM impacts across literature, as recorded in the TDM inventory. Specific outliers are called out by literature source with brief context. Source: NREL

Preliminary Scenario Results

The project team used TEMPO to model the preliminary scenarios that were developed to assess and examine the impacts of shifting household urbanities (densities). The "Baseline" (or "Base") scenario assumes no shift in household urbanities over time. The "Baseline + Growth" scenario assumes a modest growth in urbanized housing (urban, secondary city, and suburban densities). Preliminary simulations found a ±4% variation in 2050 VMT and ±3% variation in 2050 light-duty vehicle (LDV) stock across the spectrum of scenarios. Table II.7.1 summarizes the household shifts by 2050 vs. the Baseline scenario for the rural and urban housing densities which are at the end of the spectrum (see Figure II.7.1), alongside the changes in VMT and LDV stock by 2050 vs. the Baseline. Figure II.7.3 displays the VMT by year until 2050 for each of the modeled scenarios. Note that because these are preliminary scenarios, they are modeled at a lower sampling rate in TEMPO, which can create more year-over-year variation in simulations. Final scenario simulations will utilize high sampling rates to minimize noise in underlying mobility needs.

Table II.7.1 Summary of Household Shifts, VMT Change, and LDV Stock Change by 2050 Relative to the Baseline from Preliminary TEMPO Urbanity Shift Scenarios

Scenario	Household Shifts by 2050 vs. Base (rural and urban only)	VMT Change by 2050 vs. Base	LDV Stock Change by 2050 vs. Base
Baseline + Growth	-9.8% rural; +5.5% urban	-0.7%	-0.8%
Extreme Decentralization	+5.2% rural; -25% urban	+2.1%	+1.2%
Moderate Decentralization	+2.6% rural; -12% urban	+0.5%	+0.6%
Suburbanization	-8.4% rural; -1.1% urban	-0.7%	-0.4%
Moderate Urbanization	-4.9% rural; +14% urban	-0.9%	-0.9%
Extreme Urbanization	-9.8% rural; +28% urban	-2.2%	-1.7%

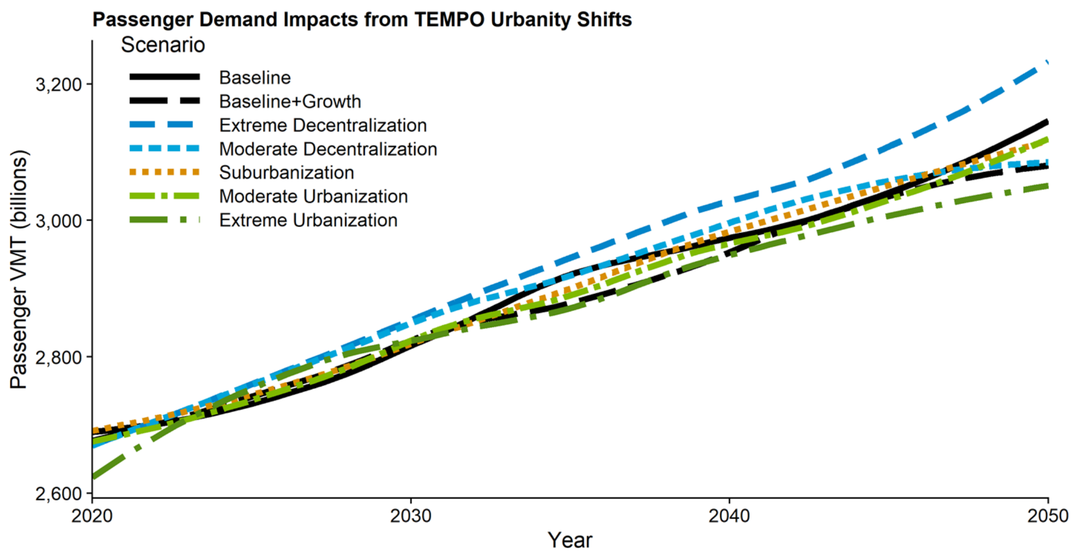

Figure II.7.3 Summary of TDM impacts on VMT across literature, as recorded in the TDM inventory. Source: NREL

Conclusions

To date, this project has focused on a comprehensive literature review of TDM strategies in the United States, development of an inventory of data points from this literature review, and preliminary scenario design and modeling in TEMPO to explore impacts of changing household density patterns. The preliminary findings show only marginal impacts to total household VMT (±4%) and LDV stock (±3%) if the projected urbanity of households evolves differently toward more decentralized (less dense) or more urbanized (denser) development by 2050. Future work will utilize TEMPO to explore impacts of changing transit parameters (changing transit availability, cost, and service), diverse levels of future tele-travel (e.g., tele-work, tele-health), and synergies with biking, walking, and micromobility adoption.

References

1. Hoehne, Christopher, Matteo Muratori, Paige Jadun, Brian Bush, Arthur Yip, Catherine Ledna, Laura Vimmerstedt, Kara Podkaminer, and Ookie Ma. 2023. "Exploring Decarbonization Pathways for USA Passenger and Freight Mobility." *Nature Communications* 14(1): 6913. https://doi.org/10.1038/s41467-023-42483-0.

2. Muratori, Matteo. 2018. "Impact of Uncoordinated Plug-in Electric Vehicle Charging on Residential Power Demand." *Nature Energy* 3(3): 193–201. https://doi.org/10.1038/s41560-017-0074-z.

3. Milovanoff, Alexandre, I. Daniel Posen, and Heather L. MacLean. 2020. "Electrification of Light-Duty Vehicle Fleet Alone Will Not Meet Mitigation Targets." *Nature Climate Change* 10(12): 1102–7. https://doi.org/10.1038/s41558-020-00921-7.

4. Moody, Joanna, Elizabeth Farr, Marisa Papagelis, and David R. Keith. 2021. "The Value of Car Ownership and Use in the United States." *Nature Sustainability* 4(9): 769–74. https://doi.org/10.1038/s41893-021-00731-5.

5. NREL. n.d. "TEMPO: Transportation Energy & Mobility Pathway Options Model." Accessed 2023. https://www.nrel.gov/transportation/tempo-model.html.

6. Muratori, Matteo, Paige Jadun, Brian Bush, Chris Hoehne, Laura Vimmerstedt, Arthur Yip, Jeff Gonder, Erin Winkler, Chris Gearhart, and Douglas Arent. 2021. "Exploring the Future Energy-Mobility Nexus: The Transportation Energy & Mobility Pathway Options (TEMPO) Model." *Transportation Research Part D: Transport and Environment* 98 (September). https://doi.org/10.1016/j.trd.2021.102967.

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III Powertrain Choice and Infrastructure Use

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

Ruixiao Sun, Principal Investigator
Oak Ridge National Laboratory
PO Box 2008, MS6472
Oak Ridge, TN 37831
E-mail: sunr@ornl.gov

Ranjan Bose, Co-Principal Investigator
Oak Ridge National Laboratory
PO Box 2008, MS6472
Oak Ridge, TN 37831
E-mail: boserk@ornl.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

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Project Introduction

Modeling vehicle market dynamics is crucial for the U.S. Department of Energy's (DOE) mission and its stakeholders. Modeling facilitates a better understanding and quantification of the future value of ongoing research and development (R&D) in energy transition issues. R&D investments in advanced vehicle technologies are often justified and prioritized because of the need to understand and address these technologies' impacts, such as changes in energy consumption, consumer costs, and greenhouse gas emissions. Estimating these impacts requires an understanding of associated market trends (e.g., consumer adoption). However, there are divergent perspectives among consumers, engineers and scientists, and suppliers. Suppliers, in particular, must strike a balance between profit, risk mitigation, and public image. These varying viewpoints, both individually and collectively, pose challenges in modeling supplier behavior and consumer acceptance of advanced vehicle technologies.

The Transportation Energy Evolution Modeling (TEEM) program (https://teem.ornl.gov/) developed the spreadsheet-based Market Acceptance of Advanced Automotive Technologies (MA3T) model and its derivatives to simulate market penetration and dynamics for advanced vehicle technologies in transitions toward energy-efficient vehicle and mobility technologies. The MA3T model analyzes how financial and non-financial attributes regarding technology, infrastructure, consumers, and policies affect the market dynamics in terms of sales and stocks for advanced automotive technologies. The model also determines the resulting impacts on the environment (i.e., greenhouse gas and pollutant emissions), energy (i.e., annual energy demand by vehicle type and mode), economy (i.e., consumer surplus), and policy.

The success of the Vehicle Technologies Office (VTO) Analysis investment in the MA3T model has been validated by its expanded application and adaptation, sponsored by entities such as the International Institute for Applied Systems Analysis and the DOE Office of Energy Efficiency and Renewable Energy (EERE). Supporting EERE entities include VTO Energy Efficient Mobility Systems, the Hydrogen and Fuel Cell Technologies Office, and the Bioenergy Technologies Office. The TEEM team has also contributed significantly to academic literature, publishing more than 90 peer-reviewed articles, including five in Fiscal Year (FY) 2023 (see Key Publications section and others in [1]).

Objectives

The TEEM project's primary objective is to offer a range of market dynamics models that support the technoeconomic evaluation of VTO technologies, aligning with VTO's technological and research interests. It is crucial to comprehend how the market responds structurally to new technologies. Modeling the organic adoption of these technologies serves as a vital bridge between technology R&D and its real-world impacts. By applying decision science theories, these market dynamics models become indispensable tools for analyzing the impact of VTO technologies and generating insights for R&D activities. The development objectives of these models include the following:

- Covering a broad technology scope of U.S. light-duty vehicles (LDVs), non-LDVs, private vehicles, and commercial vehicles; shared mobility; and connected and automated vehicles.
- Providing a comprehensive view, considering consumer behavior, technology, policy, and infrastructure factors.
- Ensuring user-friendliness for third-party users.
- Establishing model credibility through systems dynamics validation and peer-reviewed publications.
- Facilitating collaboration by utilizing existing models and engaging with academia and industry.

Approach

The core of the TEEM program is the MA3T model, which specializes in modeling market dynamics and paradigm shifts for advanced vehicle technologies. MA3T quantifies consumer preferences through a generalized cost framework that encompasses both monetary and non-monetary factors. What sets MA3T apart from other vehicle market models are its rich technological detail, detailed consumer segmentation, daily distance distribution, and comprehensive characterization of range–infrastructure dynamics.

Built on a nested multinomial logit method, MA3T predicts purchase probabilities for 40 choices, including 20 powertrain technologies for each of two vehicle size classes: passenger cars and light-duty trucks. MA3T considers U.S. household users, segmented into 9,180 customer groups based on factors such as state, residential areas, attitudes toward novel technologies, driving patterns, and recharging situations. The analysis is structured around five segments based on the adoption timelines: Innovators, Early Adopters, Early Majority, Late Majority, and Laggards. The model characterizes daily driving distance variations using the Gamma distribution [2], validated with real-world travel data, and models the impact of various charging options, range anxiety for electric vehicles, and infrastructure effects on the appeal of plug-in electric vehicles and alternative fuels. Furthermore, MA3T projects market dynamics up to 2050, capturing the temporal interplay between market penetration, product diversity, and associated risks.

Additionally, the team has addressed knowledge gaps and developed methods for analyzing transportation energy, optimizing heterogeneous electric ranges of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles, linking dynamic wireless charging's value with diverse wired charging technologies, and quantifying the impacts of free charging on BEV purchase behaviors. Various quantitative tools and models were developed to enhance the capabilities of the MA3T model. With sponsorship from EERE programs and external organizations, the TEEM modeling scope has expanded from the U.S. LDV market to include medium- and heavy-duty vehicles (MHDVs), shared mobility, automated vehicles, and even global markets. With VTO Analysis program support, Oak Ridge National Laboratory (ORNL) and the University of Tennessee, Knoxville, are collaborating to represent the used vehicle market in MA3T.

In FY 2023, the team primarily focused on the following:

- Optimizing BEV range with lightweight considerations, building a physics-based energy consumption model, and associating it with a statistics-based model based on travel surveys.
- Analyzing the cost–benefit of charging technologies on BEVs, continuing to develop the Battery Run-down under Electric Vehicle Operation (BREVO) model, which links the driver's travel pattern model with the physics-based battery degradation and powertrain energy consumption model.
- Developing the Truck Choice model through standalone fundamental studies; generating results on day cabs, transit buses, and sleepers for internal combustion engine vehicles and electric vehicles with binary total cost of ownership decisions; and planning to expand the model to fuel cell vehicles and more technologies by updating the algorithms to a multi-choice model.
- Improving the representation of new and used vehicle market dynamics, continuing model development, and generating empirical insights based on work by the University of Tennessee, Knoxville.

Results

Determining Optimal Electric Range by Considering Impacts of Electric Vehicle Lightweighting on Perceived Ownership Cost

The team developed a quantitative method that optimizes the electric range of BEVs by combining physics-based energy consumption and statistics-based models. We introduced a perceived cost of ownership (PCO) model, assessing the cost-effectiveness of lightweighting for BEV range extension based on factors such as income-dependent daily range limitations, driving patterns, and technology costs. Results suggest that lightweighting is economically viable for consumers with higher daily range requirements and intensive driving habits, but more lightweighting or extended electric range may not always be required. Notably, simulation results for the top ten best-selling BEVs in the 2021 U.S. market, as shown in Table III.1.1, indicate that, from a PCO perspective, more lightweighting or extended electric range is not necessarily needed for all BEV models. For Vehicle Models #1 through #4 and #10, the optimized result is increased vehicle weight and reduced electric range compared to the current model features. This is because using less lightweighting technology in the BEV design can help reduce vehicle price (even if the increased weight compromises electric range), resulting in overall PCO savings. Conversely, it is suggested that Vehicle Models #5, #7, #8, and #9 would benefit from further lightweighting to reduce PCO relative to the current model design. However, Vehicle Model #6 is an exception; its slight weight reduction and range decrease result in minimal PCO savings, indicating that lightweighting isn't always advantageous for BEVs. For more detailed information, please refer to our published article [3].

Table III.1.1 Simulation Results for Top Ten Best-Selling BEVs in the 2021 U.S. Market

No.	Vehicle Maker	Vehicle Model	Current Electric Range (miles)	Optimized Weight Changes (kg)	Optimized Electric Range Changes (miles)	Incremental PCO Saved ($)
1	Tesla	Model Y Long Range AWD	326	+34	-3	26
2	Tesla	Model 3 Long Range AWD	353	+107	-10	285
3	Ford	Mach-E	230	+163	-8	476
4	Chevrolet	Bolt EV	259	+145	-9	575
5	Volkswagen	ID.4 AWD Pro	260	-75	+4	129
6	Nissan	LEAF	149	-31	-1	26

No.	Vehicle Maker	Vehicle Model	Current Electric Range (miles)	Optimized Weight Changes (kg)	Optimized Electric Range Changes (miles)	Incremental PCO Saved ($)
7	Audi	Audi e-tron Quattro Sportback	218	-123	+4	396
8	Porsche	Taycan 4S Perf Battery	200	-106	+4	466
9	Tesla	Model S Long Range	402	-45	+5	96
10	Hyundai	Kona Electric	258	+93	-4	243

BREVO Model Development

This task is to develop a model for estimating battery capacity degradation based on real-world end-use factors. The BREVO model provides crucial information for consumers and BEV manufacturers on range anxiety, BEV battery design, and decision support of the battery warranty. The model links the driver's travel patterns to physics-based battery degradation and powertrain energy consumption models. It aims to quantify the impacts of charging and driver travel patterns on battery degradation and to provide insights to inform stakeholders involved in BEV battery design and the electric vehicle market. The open-source code is published in GitHub (https://github.com/ous-ornl/brevo), and a paper on estimating long-term impacts on battery degradation using the BREVO model was published in *Journal of Power Sources* in FY 2023 [4]. In this study, a comparison of the impacts of different charging levels on battery aging as shown in Figure III.1.1(a) revealed that, over a 10-year span, daily direct current fast charging (60 kW) could lead to up to 22% less battery capacity compared to daily Level 1 charging (1.8 kW). The project also used BREVO to examine the impact of temperature differences between New England area and Los Angeles area on vehicle battery lifetime for miles driven as shown in Figure III.1.1(b). The battery thermal management system can delay battery degradation by approximately 0.5% in the New England area. The model controls simulations with the same BEV, the same random driver, and identical travel patterns; the only variation is in the areas with different temperature trend profiles (New England vs. Los Angeles). The model indicates that battery capacity in Los Angeles is 6% higher than in New England, demonstrating that warmer ambient temperatures enhance BEV battery usage.

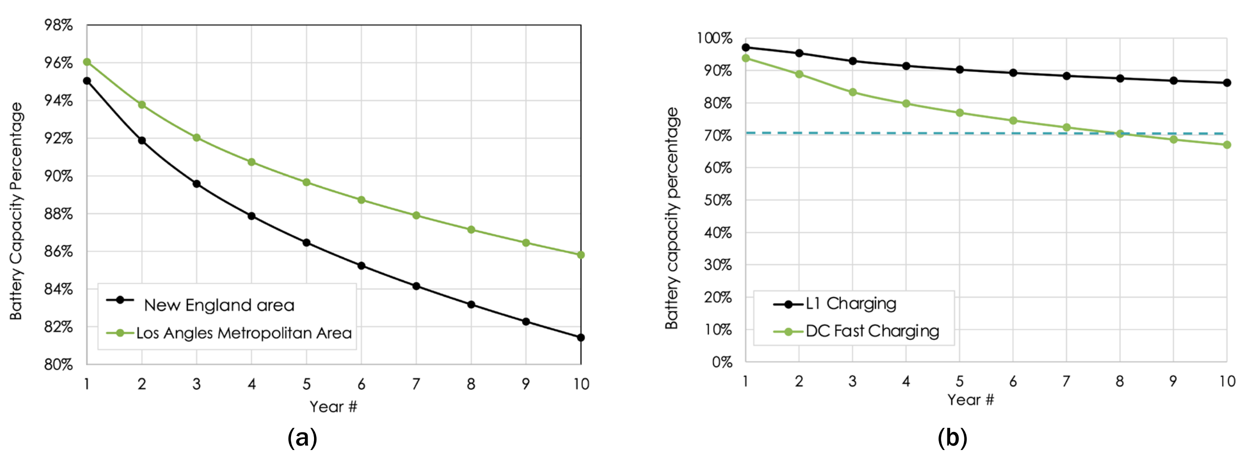
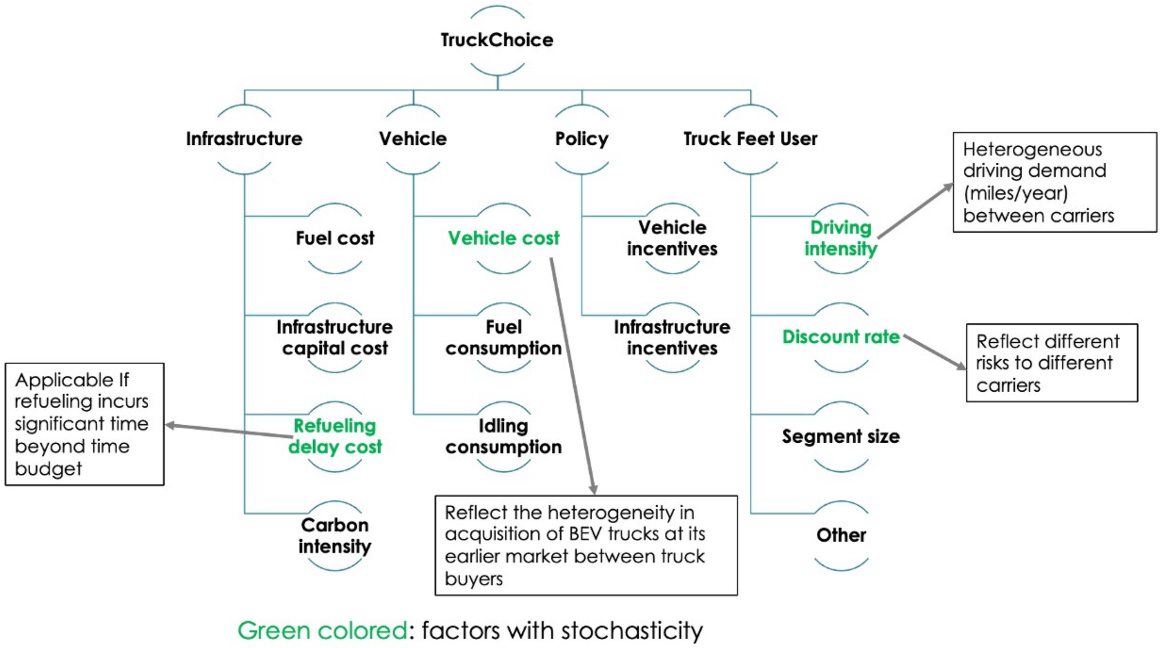


Figure III.1.1 (a) **Remaining battery capacity by year and** (b) **remaining battery capacity by area. Source: ORNL**

Truck Choice Model: An Agent-Based Model for the MHDV Market in the United States

Building upon the foundations of the advanced vehicle market transition model for LDVs, the MA3T model, our team developed the MHDV version: the Truck Choice model. This model aims to provide valuable insights into the potential future adoption of advanced vehicle technologies in the MHDV sector. Employing a multinomial logit model at its core, as depicted in Figure III.1.2, the Truck Choice model simulates advanced vehicle choices across diverse MHDV fleet segments. These simulations are based on future projections of vehicle technology development, alternative fuel technology R&D (e.g., battery research), fleet segmentation



properties, policies, and refueling infrastructure expansions.

Figure III.1.2 Structure of the Truck Choice model. Source: ORNL

The model's versatility extends to evaluating market acceptance of alternative fuel technologies, including BEVs and fuel cell hydrogen electric vehicles, alongside conventional fuels such as diesel, gasoline, and natural gas. By utilizing a multinomial logit approach, the Truck Choice model captures the complex decision-making processes of MHDV fleet operators and owners in adopting advanced vehicle technologies. It assesses a range of factors, such as vehicle costs, refueling efficiency, refueling costs, charging availability, and the influence of government incentives on technology adoption. This comprehensive modeling approach allows stakeholders to gauge the impact of cutting-edge technologies on the future of the MHDV sector. Figure III.1.2 illustrates the structure of the Truck Choice model, highlighting its robust framework for capturing market dynamics and technology adoption in the MHDV market.

MA3T–Used Vehicle Model Development

During FY 2023, our team completed development of the Used Vehicle model (UVM), designed for integration into the MA3T model. This integration signifies a major advancement in forecasting capabilities, as the UVM utilizes baseline forecasts of new vehicle sales from the MA3T model to effectively project the evolution of used vehicle stock. The UVM's methodology is reliant on the MA3T model's projections, where it assesses vehicle survival rates and the impacts of new vehicle sales fluctuations on the used vehicle market, as shown in Figure III.1.3. This method ensures a comprehensive and interconnected analysis of both new and used vehicle markets. Operationally, the UVM necessitates user-defined parameters, including coefficients to project future vehicle scrappage rates [5]. It then utilizes these inputs alongside the MA3T baseline projections—categorized by calendar year, vehicle type, and technology—to calculate changes in vehicle stock. The UVM's true strength lies in its ability to analyze various MA3T vehicle sales scenarios influenced by policy, technology, or economic changes. The UVM adeptly predicts shifts in used vehicle scrappage, thereby influencing the composition and utilization of the used vehicle fleet [6]. The model's capacity to analyze the interplay between new and used vehicle markets is critical for informing policies aimed at expediting the retirement of legacy gasoline vehicles.

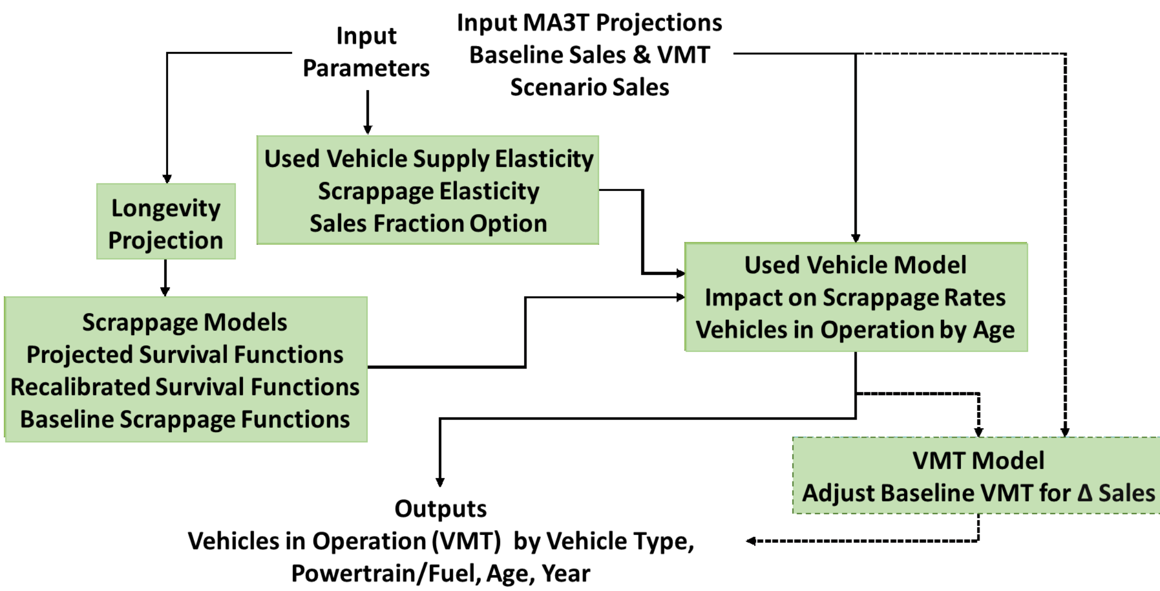


Figure III.1.3 Flowchart of the UVM. Source: University of Tennessee

Conclusions

In FY 2023, the TEEM team undertook a multifaceted research agenda, which included the refinement of BEV range optimization with a focus on lightweighting strategies, a comprehensive cost–benefit analysis of various charging technologies for BEVs, development of the innovative Truck Choice model tailored to the MHDV market, and a deep dive into the intricate dynamics of used vehicle markets. These studies supported the continual improvement of the MA3T model and its derivatives, such as the MA3T–UVM state-level analysis. The team published six articles on these subjects, providing a solid foundation for future research aimed at further advancing the MA3T model suite, ultimately contributing to a more integrated analysis of emerging energy-relevant technologies.

Key Publications

1. Greene, David L. and Benjamin Leard. 2023. “Statistical Estimation of Trends in Scrappage and Survival of US Light-duty Vehicles.” Howard H. Baker, Jr. Center for Public Policy, The University of Tennessee, Knoxville. https://baker.utk.edu/wp-content/uploads/2023/03/Formatted-Vehicle-Scrappage-and-Survival_Single-Column_7Mar23.pdf.

2. Leard, Benjamin and David Greene. 2023. “Coordinating the electric vehicle transition and electricity grid decarbonization in the US is not essential to achieving substantial long-term carbon dioxide emissions reductions.” Environmental Research Letters 18(7): 074035.

3. Li, Wan, Zhenhong Lin, Shiqi Shawn Ou, and Boyu Wang. 2023. “Deployment priority of public charging speeds for increasing battery electric vehicle usability.” Transportation Research Part D: Transport and Environment 124, 103943.

4. Ou, Shiqi, Shengyong Zhang, Zhenhong Lin, and Stacy Davis. 2023. “A method for determining optimal electric range by considering electric vehicle lightweighting on perceived ownership cost.: Journal of Cleaner Production 385, 135606.

5. Ou, Shiqi. 2023. “Estimate long-term impact on battery degradation by considering electric vehicle real-world end-use factors.” Journal of Power Sources 573, 233133.

References

1. TEEM. n.d. "TEEM Publications." https://teem.ornl.gov/publications.shtml.

2. Lin, Z., and C. Liu. 2015. "MA3T—modeling vehicle market dynamics with consumer segmentation." In proceedings of the 2015 U.S. DOE Hydrogen Program and Vehicle Technologies Program Annual Merit Review Meeting, Arlington, Virginia: 8–12.

3. Ou, Shiqi, Shengyong Zhang, Zhenhong Lin, and Stacy Davis. 2023. "A method for determining optimal electric range by considering electric vehicle lightweighting on perceived ownership cost." *Journal of Cleaner Production* 385, 135606.

4. Ou, Shiqi. 2023. "Estimate long-term impact on battery degradation by considering electric vehicle real-world end-use factors." *Journal of Power Sources* 573, 233133.

5. Greene, David L., and Benjamin Leard. 2023. "Statistical Estimation of Trends in Scrappage and Survival of US Light-duty Vehicles." Howard H. Baker, Jr. Center for Public Policy, The University of Tennessee, Knoxville. https://baker.utk.edu/wp-content/uploads/2023/03/Formatted-Vehicle-Scrappage-and-Survival_Single-Column_7Mar23.pdf.

6. 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, The University of Tennessee, Knoxville, for the Transportation Science Division of Oak Ridge National Laboratory. https://baker.utk.edu/publication-cetep-transportation/a-statistical-analysis-of-trends-in-light-duty-vehicle-scrappage-and-survival-2003-2020/.

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Other project team members that we would like to acknowledge are David Greene, Ben Leard, Wan Li, and Shiqi (Shawn) Ou.

III.2 Agent-Based, Bottom-Up Medium- and Heavy-Duty Electric Vehicle Economics, Operation, Charging, and Adoption (Colorado State University)

Thomas H. Bradley, Principal Investigator
Colorado State University
Campus Delivery 6029
Fort Collins, CO 80523
E-mail: THB@colostate.edu

Erika Gallegos, Co- Principal Investigator
Colorado State University
Campus Delivery 6029
Fort Collins, CO 80523
E-mail: Erika3@colostate.edu

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

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

Project Introduction

Medium-duty and heavy-duty (MDHD) vehicles account for more than a quarter of U.S. road transportation fuel use and carbon dioxide emissions, with a projected increase in energy consumption of 11% by 2050 [1]. Plug-in electric vehicle (PEV) technologies are a key decarbonization technology, but PEVs face technical challenges in satisfying operational requirements for some MDHD sectors. Such complications include limits to driving range, long recharging times, and the need for high-power charging infrastructure.

In considering the future adoption of PEV MDHD vehicles, we must recognize that the decentralized decision-making of fleet purchasers, electric vehicle (EV) supply equipment and vehicle manufacturers, energy system stakeholders, and local policymakers will continue to play key roles in defining electric MDHD (eMDHD) availability and uptake. The timelines under which PEVs will become suitable and cost-competitive in different MDHD applications will differ with different vocations, vehicle types, and U.S. regions. Recent analysis has suggested that electric 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 [2], [3], [4], but key MDHD stakeholders have incomplete access to information and resources to inform their decision-making. Together, this disparate and decentralized nature of the MDHD marketplace 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.[1] The first modeling tool is a fleet-level technoeconomic analysis model capable of estimating energy use and associated environmental and cost impacts for electrified and conventional vehicles of any MDHD vocation. The tool uses real-world cost and operations data and includes approaches to optimizing schedules for charging and/or vehicle dispatch. The second modeling tool is a system-level, bottom-up, agent-based adoption model (ABM) capable of generating

[1] Vehicle Technologies Office Fiscal Year 2021 Research Funding Opportunity, Area of Interest 8, which focuses on electrification data analysis of road transportation vehicles.

geographically resolved estimates of market projections for MDHD vehicles and charging infrastructure. These tools have been developed together to serve dual purposes as analysis tools for researchers and decision-support tools for decision-makers in the MDHD system. 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. This paper presents the methods and approaches for the ABM, with details of MDHD PEV economics and operations available in previous work.

Approach

Agent-Based PEV Adoption Modeling

ABM is an individual-level modeling technique in which "agents" are modeled to operate autonomously, influencing 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 on either demand or supply, but the market will be driven by the interaction between supply and demand, either 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, in which 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 [6], [7].

To address these dynamics, agents in our model are of three types: (1) fleet operators, (2) manufacturers of vehicles, and (3) utility and infrastructure managers. Policy decisions are treated as inputs to the adoption model. Each of these agent varieties makes decisions in pursuit of individualistic objectives, based on a 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 public fast-charging stations improves the suitability and TCO of PEVs for ride-sharing 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 provoking them to adopt PEVs. These and many other means of feedback and diffusion can be investigated via ABM.

Decision-Making Models and Data Sources

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 [8]. 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 incorporates 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 [9]. 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.

Adoption Process Model

Agents are organized in networks, one each for fleets, utilities, and original equipment manufacturers (OEMs). Fleet agents own and control vehicles and charging infrastructure, about which they form and share opinions. Utility agents control the costs of installing and operating electric infrastructure. OEM agents control the attributes and availability of vehicles, including costs. To this ABM population, we apply a conceptual framework for alternative-fuel vehicle adoption by commercial fleets based on interviews with heavy-duty (HD) vehicle fleet managers [10]. The theories underpinning the framework account for (1) how innovations spread across social networks (Diffusion of Innovations theory), (2) factors particular to organizational adoption (Technology–Organization–Environment framework), and (3) the roles played by individuals within the organization, including decision-makers and those directly operating the new technologies. The framework they present consists of an adoption process and, within that process, a characterization of the factors influencing the decision to adopt. The following sections describe how each step in the process is modeled.

Awareness

Agents' state of awareness is binary, that is, they are either unaware or aware of each vehicle available to them. They can gain awareness either through the advertising and outreach efforts of OEMs and others, or through interactions with other fleets. Advertising is modeled as a stochastic process, where all agents that are unaware of a particular OEM have a probability of discovering them each year. Interactions between agents are modeled in detail.

Consideration

Fleets will consider adopting a vehicle if they perceive it to be capable of satisfying their operational requirements. These requirements are represented in terms of range and cargo/passenger capacity. A vehicle will not be considered for adoption if it has less range than the longest distance traveled in a day by existing vehicles, or if it has less cargo/passenger capacity than the greatest capacity used by existing vehicles. Vehicles perceived to be operationally suitable are also subjected to economic analysis. Finally, agents assess the relative utility of all the vehicles of which they are aware.

Adoption Decision

Having evaluated vehicles for suitability and subjectively assessed them, agents decide whether to replace each existing fleet vehicle and what the replacement vehicle should be. (Vehicles that were purchased within the previous eight years are never replaced.) Every existing vehicle is paired with the highest-utility option suitable for replacing it and entered into the equation below to find the replacement probability:

$$p_{\text{replace}} = \begin{cases} 1 & u_1 \geq u_0 \\ 10^{k(u_1 - u_0)} & u_1 < u_0 \end{cases}$$

where u_0 is the utility of the existing option, u_1 is the utility of the potential replacement, and k is a constant. Thus, if the potential replacement is perceived to be equal or superior to the existing vehicle, it is always adopted. Otherwise, it may still be adopted, but with a probability that decreases sharply with its perceived inferiority. This enables fleets to adopt vehicles as pilot projects, to gain information and evaluate feasibility. (Each vehicle option can only be "piloted" once.)

Implementation and Confirmation

Finally, fleets procure and operate new vehicles and charging infrastructure. In the implementation step, fleets sell vehicles that are being replaced, procure new vehicles, and design a minimum-cost EV charging system, accounting for existing charging assets, to enable all BEVs to complete their drive cycles. It is assumed that all BEV charging is performed at the fleet's home base. For the confirmation step, fleet agents record observations of all attributes of all vehicles they own, old and new.

In summary, an ABM 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 (e.g., TCO and up-front cost) comprise a significant effort of supporting research and will be initialized based on results of studies in the literature correlating decision preference with fleet characteristics [11].

Results

In Budget Period (BP) 1, the capital costs modeling and operating costs microsimulation tools were developed, validated, and demonstrated. These results were presented in the FY 2022 Vehicle Technologies Office Annual Progress Report [12]. In BP 2, these costs and modeling tools were integrated into the ABM software, and this software was demonstrated and validated for modeling of adoption of MDHD EVs.

Framework-Level ABM Results

When the tools developed in BP 1 are combined with models of learning and opinion formation, the result is an ABM framework that can model the perceptions, learning, and decision-making of agents, thereby meeting the requirements of the proposed ABM adoption framework.

Figure III.2.1 provides a visualization of how agents form perceptions on the basis of observations, illustrating an example of the maintenance cost calculation that can be performed for all of the agents and trials that are in the ABM framework. The figure shows observations pertaining to maintenance cost for two vehicle options, an internal combustion engine vehicle and a BEV, where more heavily weighted observations are shown as larger points. Colors identify the means by which observations were made. The overall distribution of observations is shown as a box-and-whisker plot, with the median as a line and the mean as a circle in the box. The vertical axis shows how values map to subjective assessments, on a scale of 0 to 5, with lower maintenance costs mapping to higher subjective assessments. Figure III.2.1 exemplifies how ABM models can realize a distribution of perceptions, learning, and decision-making for a diverse set of agents in the simulation.

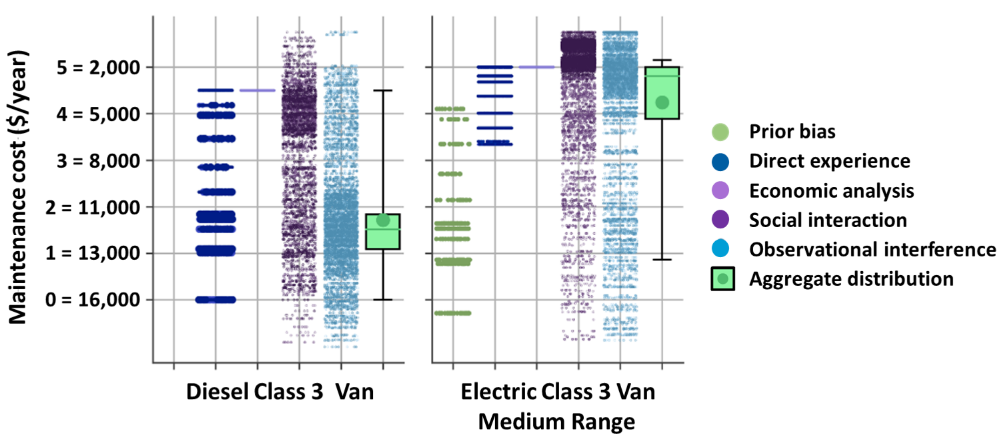

Figure III.2.1. Visualization of how agents form perceptions on the basis of observations. Source: Colorado State University

ABM Adoption Results

The ABM is then utilized to test the effects of various heterogeneities on the adoption of PEVs in MDHD fleets. To exercise this model, three key experiments within the ABM framework are conducted to understand the influence of weight class heterogeneity, preference heterogeneity, and range option heterogeneity on EV adoption rates. Although these results consider only a small pool of 10 fleet agents, the results of this small problem provide examples of the types of insights that can be extracted only from ABM-based models (in contrast to other EV adoption models [13]).

1. **Vehicle Class Heterogeneity:** The first experiment tested how the electrification of lower weight classes (more economically and operationally feasible) influences the electrification of higher weight classes. The hypothesis was that the adoption of HD vehicles would accelerate if HD vehicle fleet operators observed the adoption of PEVs within medium-duty (MD) vehicles. As illustrated in Figure III.2.2, results show that interaction with and learnings from MD fleets accelerate PEV adoption among HD fleets, indicating the importance of social learning in the modeled PEV adoption processes.

Scenario	Description
(a)	No interaction between MD and HD
(b)	Interaction between MD and HD

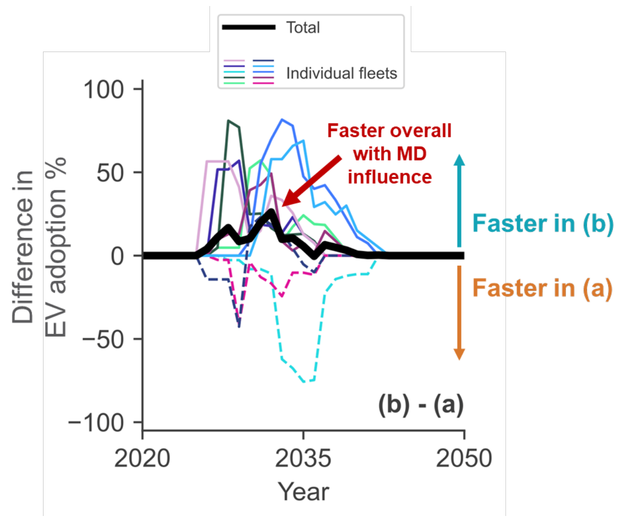

Figure III.2.2 Visualization of the incremental adoption rate for HD PEVs for each year in the period 2020–2050 under two scenarios of MD fleet to HD fleet interaction. Under scenario (a), MD and HD fleets share no learnings. Under scenario (b), HD fleets learn from experiences of MD fleets and adopt PEVs at a higher rate than in scenario (a). Source: Colorado State University

2. **Preference Heterogeneity:** This part of the study examined how variations in the range and variety of decision-making preferences within a population affect electrification outcomes. The results supported the hypothesis that a population with average decision preferences will adopt EVs more rapidly if it includes agents with a diversity of EV preferences, as EV-positive early adopters can normalize the technology and share their positive experiences for the rest of the population. Results are not illustrated here in the interest of brevity.

3. **Range Option Heterogeneity:** The final experiment analyzed how the availability of different electric range options affects MD PEV adoption rate. This work hypothesized that a greater variety of electric range options would allow fleets to tailor their vehicles to the needs of their vocations, thereby leading to faster adoption. As illustrated in Figure III.2.3, relative to adoption scenarios where only a default short-range MD PEV with 50 miles of range is available, the addition of more options within the same vehicle platform led to accelerated adoption. Further increasing the number of options led to a diminishing effect on adoption rate.

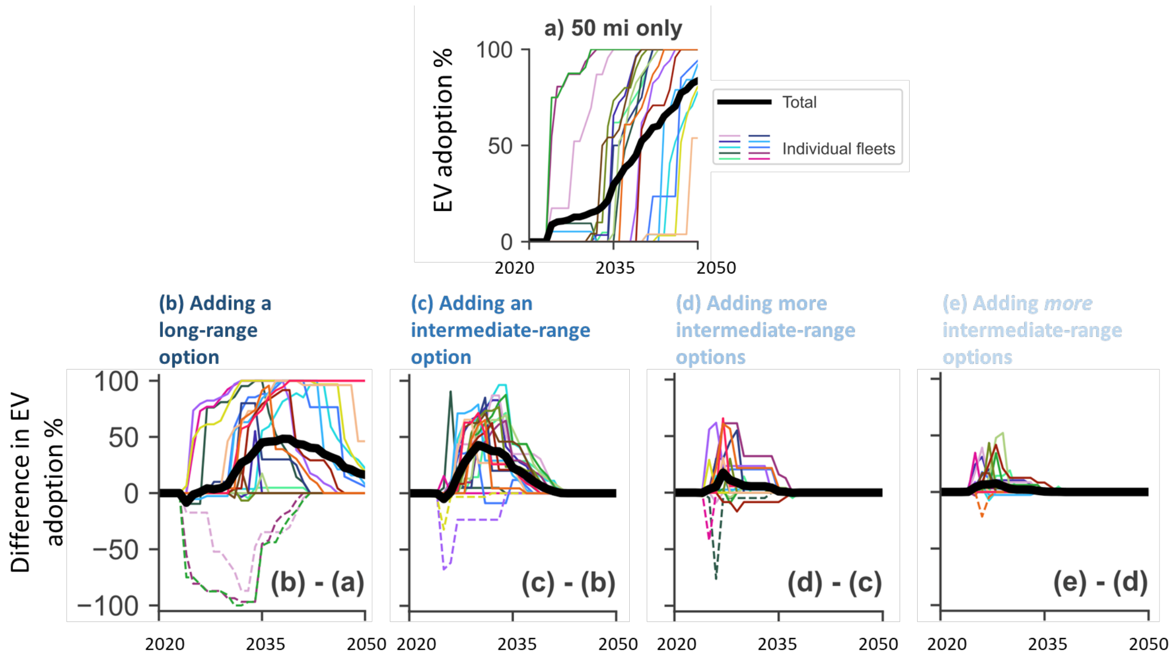

Figure III.2.3 Illustration of the MD PEV adoption rate results for a variety of scenarios for the period 2020–2050. At top is scenario (a) modeling adoption for a small-range vehicle. Accelerated adoption of PEVs in scenarios (b) through (e) is observable by the total difference in EV adoption being plotted at values greater than zero because of diminishing effects. Source: Colorado State University

Overall, the ABM results demonstrate the dynamics of fleet electrification, influenced by a range of factors from social influences on technical specifications. The results underscore the complexity of EV adoption and the importance of considering a variety of factors beyond economic calculations in understanding and predicting fleet behaviors.

Conclusions

In this research, bottom-up modeling is employed to simulate EV adoption within MDHD fleets, considering the technoeconomic factors and operational constraints that influence electrification. The ABM demonstrates the ability to simulate complex adoption dynamics across diverse fleet networks. Despite the sophisticated nature of bottom-up models and their potential to inform policy and planning, the approach is tempered by the challenges of extensive data requirements, potential unavailability of proprietary information, and computational constraints that limit the complete representation of real-world systems. Nevertheless, the model promises to enrich our understanding of fleet electrification dynamics and supports the development of nuanced strategies for advancing electric transportation.

Key Publications

1. Ouren, F, D. Trinko, T. Coburn, S. Simske, and T. H. Bradley. 2023. “Developing a profile of medium- and heavy-duty electric vehicle fleet adopters with text mining and machine learning.” Renewable Energy Focus 46: 303–312.

2. Ouren, F., and T. Coburn. 2023. “Developing a Profile of Medium- and Heavy-Duty Electric Fleet Adopters with Text Mining and Machine Learning.” DOE/LANL Conference on Data Analysis, Santa Fe, NM.

3. Trinko, D., N. Horesh, E. Porter, J. Dunkley, E. Miller, and T. H. Bradley. 2023. “Transportation and electricity systems integration via electric vehicle charging-as-a-service: a review of techno-economic and societal benefits.” Sustainable and Renewable Energy Reviews 175 (April), 113180.

References

1. 21st Century Truck Partnership (21CTP). 2019. "21st Century Truck Partnership Research Blueprint." https://www.energy.gov/sites/prod/files/2019/02/f59/21CTPResearchBlueprint2019_FINAL.pdf.

2. Phadke, A., et al. 2021. "Why Regional and Long-Haul Trucks are Primed for Electrification Now." Lawrence Berkeley National Laboratory. https://eta-publications.lbl.gov/sites/default/files/updated_5_final_ehdv_report_033121.pdf.

3. Baral, N. R., Z. D. Asher, D. Trinko, E. Sproul, C. Quiroz-Arita, T. H. Bradley. 2021. "Biomass feedstock transport using fuel cell and battery electric trucks improves lifecycle metrics of biofuel sustainability and economy." *Journal of Cleaner Production* 279, 123593. https://doi.org/10.1016/j.jclepro.2020.123593.

4. Biresselioglu, M. E., M. Kaplan, and B. K. Yilmaz. 2018. "Electric mobility in Europe: A comprehensive review of motivators and barriers in decision making processes." *Transportation Research Part A: Policy and Practice* 109: 1–13. https://doi.org/10.1016/j.tra.2018.01.017.

5. U.S. Department of Energy and Clean Cities. 2012. "Plug-In Electric Vehicle Handbook for Public Charging Station Hosts." https://www.nrel.gov/docs/fy12osti/51227.pdf.

6. Anderhofstadt, B., and S. Spinler. 2019. "Factors affecting the purchasing decision and operation of alternative fuel-powered heavy-duty trucks in Germany – A Delphi study." *Transportation Research Part D: Transport and Environment* 73 (August): 87–107.

7. Forrest, K., M. MacKinnon, B. Tarroja, and S. Samuelsen. 2020. "Estimating the technical feasibility of fuel cell and battery electric vehicles for the medium and heavy duty sectors in California." *Applied Energy* 276 (October 15), 115439.

8. Kaplan, S., J. Bruber, M. Reinthaler, and J. Klauenber. 2016. "Intentions to introduce electric vehicles in the commercial sector: A model based on the theory of planned behaviour." *Research in Transportation Economics* 55 (June): 12–19.

9. Nesbitt, K., and D. Sperling. 2001. "Fleet purchase behavior: decision processes and implications for new vehicle technologies and fuels." *Transportation Research Part C: Emerging Technologies* 9(5) (October): 297–318.

10. Bae, Y., S. Mitra, and S. G. Ritchie, S.G. 2022. "Factors influencing alternative fuel adoption decisions in heavy-duty vehicle fleets," *Transportation Research Part D: Transport and Environment* 102 (January), 103150. DOI 10.1016/j.trd.2021.103150.

11. Ouren, F, D. Trinko, T. Coburn, S. Simske, and T. H. Bradley. 2023. "Developing a profile of medium- and heavy-duty electric vehicle fleet adopters with text mining and machine learning." *Renewable Energy Focus* 46: 303–312.

12. Ollia, S., J. Ward, and R. Isaacs. 2022. "2022 Annual Progress Report." U.S. Department of Energy, Vehicle Technologies Office. https://www.energy.gov/sites/default/files/2023-10/2022%20VTO%20Analysis%20Annual%20Progress%20Report%20-%20FINAL%20091223_compliant_.pdf.

13. Al-Alawi, B., and T. H. Bradley. 2013. "Review of Hybrid, Plug-in Hybrid, and Electric Vehicle Market Modeling Studies." *Renewable and Sustainable Energy Reviews* 21 (May): 190–203.

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III.3 Scalable Truck Charging Demand Simulation for Cost-Optimized Infrastructure Planning (ElectroTempo, Inc.)

Ann Xu, Principal Investigator
ElectroTempo, Inc.
4201 Wilson Blvd., Suite 300
Arlington, VA 22203
E-mail: Ann.Xu@ElectroTempo.com

Patrick Walsh, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Patrick.Walsh@ee.doe.gov

Start Date: October 1, 2021 End Date: December 31, 2024
Project Funding (FY23): $100,697 DOE share: $84,556 Non-DOE share: $16,141

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 U.S. Environmental Protection Agency has reported that:

- In 2020, medium- and heavy-duty trucks accounted for 26.3% of U.S. carbon dioxide emissions from fossil fuel combustion [1].
- About 72 million people live within 200 meters of a freight route [2].
- People of color and those with lower incomes are more likely to live near those routes [2].

Truck electrification will also present high, concentrated, and inflexible charging demand and, therefore, significant threat to the grid. According to Oncor, a Texas utility, a few customers simultaneously electrifying only a few vehicles each 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 are 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 overall objectives of the project are (1) to 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 2 (January–December 2023), the objective was to analyze cost-optimization strategies by identifying key factors influencing infrastructure and environment costs and simulating the benefits of well-designed rate structures.

Approach

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

There is currently a lack of mature models and real-world data at various stages and resolution levels in the modeling process. Therefore, 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. The project explores diverse truck data sources and develops algorithms to fuse these data sources and generate realistic synthetic data for system simulation. In this budget period, the project team automated and streamlined the transportation and grid models, independently and jointly, such that the time required to conduct a coupled infrastructure study is reduced to hours. We demonstrated an approach to reconcile the differences of spatial resolution and scale between the simulations of the two infrastructure systems.

Specifically, the team assembled ninety-six 24-hour scenarios for charging and grid simulations. We analyzed the results to identify the impact of different charging configurations on capital, operating, and environmental costs of the grid. In addition, we tested three electricity pricing strategies to identify ways to reduce such costs.

Results

The project team modularized the urban and long-haul truck charging demand models developed under Task 1. We introduced five parameters that can be used to configure a 24-hour charging demand simulation for the megaregion that includes the Dallas and Houston metropolitan areas and the Interstate 45 (I-45) corridor:

- **Charge rate:** The fixed rate (in kilowatts) at which trucks can charge at a depot
- **Season:** The time of year, which affects air conditioning/heater usage and thus energy consumption per mile of truck travel
- **Truck market adoption rate:** The percentage of all truck trips attributed to battery electric trucks
- **Charging logic:** The time of day at which trucks are assumed to begin overnight charging
- **I-45 truck charging depot location:** The location along I-45 where electric trucks have an opportunity to charge

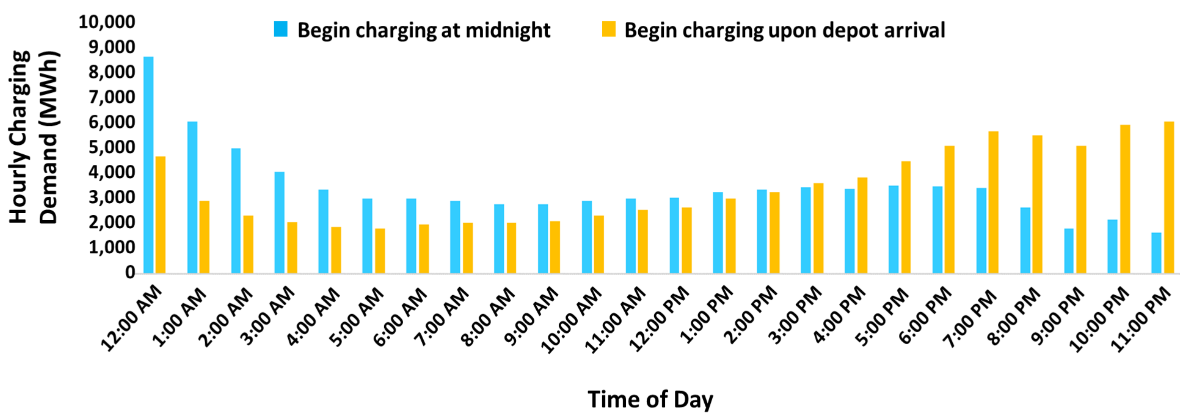
The season, market adoption rate, and I-45 depot location each affect total estimated charging demand:

- **Season:** For each truck class, we estimate a unique energy consumption rate (kilowatt-hours per mile traveled) according to battery capacity (kilowatt-hours) and range (miles). We use this rate and the modeled truck trip length (miles) to estimate energy use and charging demand, accordingly. We assume energy use per mile is roughly 14% higher in the summer and winter than in the spring and fall. Therefore, a unitless consumption factor is applied to the total energy consumption rate, based on the season: the factor is 1.2 in the summer and winter months and 1.05 in the spring and fall months.
- **Truck market adoption rate:** Total charging demand scales linearly with truck market adoption rate. We assume that under different adoption rate scenarios, the distribution of truck trips by origin and destination and time of day remains constant. We model adoption rates of 25%, 50%, 75%, and 100%.
- **I-45 depot location:** The charging logic applied to long-haul truck trips depends on the trip's origin and destination and the relative distance from one to the other, and we assume trucks will typically charge only if their state of charge is low. For instance, we assume that trucks that depart the Houston

region will not stop to charge at a depot located just outside the Houston region because they will still have a high state of charge. We model one depot near the midpoint between Houston and Dallas (about 130 miles from each city) and one relatively close to Dallas (less than 60 miles out of the city). The charging demand is estimated to be higher at the midpoint depot because the algorithm does not just factor in trips starting in Houston, but also trips that start up-stream of Houston and pass through on the way to Dallas. Trucks that were not fully charged when starting from Houston would run out of charge mid-way, which is why charging demand is estimated to be higher at the midpoint depot.

The charge rate and charging logic parameters do not influence total estimated charging demand, but they do shape the time distribution of charging demand. Figure III.3.1 depicts the impact of charging logic on the shape of the demand.

- **Charge rate:** Given a similar magnitude of demand, increasing the assumed truck charge rate at a depot concentrates demand in smaller time windows, which can increase the expected peak demand.
- **Charging logic:** Given a similar magnitude of demand, charging upon evening arrival at the depot results in lower peak demand because it is spread over several evening hours. When all overnight charging is assumed to begin at midnight, a strong peak in demand is observed at midnight.



Assumptions: 200 kW charge rate, winter/summer heat/air conditioner use, 100% market adoption, and depot at I-287

Figure III.3.1 Hourly charging demand (in megawatt-hours) by charging logic

Grid Cost Analysis

Operating Costs

We approximated the yearly change in operating cost due to the heavy-duty electric vehicle (EV) truck simulation scenarios. Since the simulation covers only a 24-hour load period, we chose a representative day that could be multiplied by 365 to get an approximate yearly operating cost increase or decrease. From the project's synthetic distribution system load data, which is from 2018, the team chose May 3, which has a daily average load of 47.7 MW. This accounts for load growth from the Electric Reliability Council of Texas yearly average of 43 MW from 2018.

Table III.3.1 presents a summary of the key findings in the operating cost analysis. The cost values were rounded to the nearest thousand dollars; cost increase (in red) is listed as positive, and cost decrease (in green) is negative. The charging scenario parameters that had the most impact on cost were charging logic, maximum charging rate, and market adoption.

The key takeaway from Table III.3.1 is that *market adoption rate is the primary driver of cost increase*, which is to be expected, but this can be reduced by using the charging logic that begins at midnight and/or increasing the maximum charging rate to 300 kW. However, as shown later in the capital cost analysis section, increasing the maximum charging rate increases the total overloads in the distribution system, increasing the capital cost of correcting these overloads.

Table III.3.1 Summary Highlights of Operating Cost Analysis

Charging Logic	Baseline Scenario Parameter	Comparison Parameter	Average Cost Difference (24-hour)	Average Cost Difference (yearly)
Both averaged	0% market adoption rate	25% market adoption rate	$607,000	$221,555,000
Both averaged	25% adoption rate	50% adoption rate	$715,000	$260,975,000
Both averaged	50% adoption rate	75% adoption rate	$775,000	$282,875,000
Both averaged	75% adoption rate	100% adoption rate	$815,000	$297,475,000
N/A	Charging upon depot arrival	Charging beginning at midnight	-$95,000	-$34,675,000
Beginning at midnight	100 kW max charging rate	200 kW max charging rate	-$25,000	-$9,125,000
	200 kW max charging rate	300 kW max charging rate	-$33,000	-$12,045,000
Upon depot arrival	100 kW max charging rate	200 kW max charging rate	-$2,000	-$730,000
	200 kW max charging rate	300 kW max charging rate	$300	$110,000

Capital Costs

To assign a dollar value to correct transmission and distribution overloads, the team used an upgrade cost of $1,250 per MW-mile for transmission lines and $2,500 for distribution lines. These numbers were derived from the average costs of around $2,500 per MW-mile of new construction for the Competitive Renewable Energy Zone projects in Texas [4] and an average line upgrade costing 30%–50% of new construction [5].

For distribution lines, the National Renewable Energy Laboratory lists the cost of new transmission construction projects as $1,200–$5,341 per MW-mile for long-distance and $2,400–$10,683 per MW-mile for lower-voltage transmission [6]. Thus, 50% of the $2,500 cost was used for transmission.

For distribution system upgrades, the cost range for lower voltage levels was used. This range was refined by using the $42,000 to $79,000 per mile of new distribution lines from T. Farmer [7] and an average distribution limit of 12 MW from Burlington Electric [8] (600 amps nominal rating and typical 13.8 kV voltage rating, minus some safety margin).

Figure III.3.2 depicts the overall capital cost trends as EV penetration increases. At low EV penetration levels, distribution costs are higher than transmission costs. As EVs approach full penetration, however, transmission costs overtake distribution costs.

Within each penetration level where the total demand is fixed, factors such as charging logic and charging rate make a difference on capital costs, especially distribution costs. Generally, higher charging rates correspond to higher distribution costs, whereas charging at midnight corresponds to lower distribution costs. These observations form a basis for rate structure design.

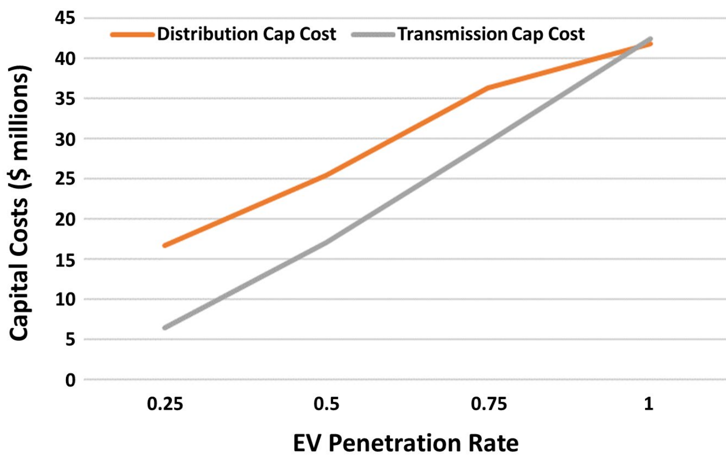


Figure III.3.2 Capital cost vs. EV penetration rate

Environmental Costs

The project team analyzed fuel cycle (tailpipe + power plant) emissions for both greenhouse gases and criteria pollutants. Because of space constraints, readers are referred to our journal publication on this topic [9].

Rate Design

To achieve the desired 20% or greater cost reduction, the project team designed three rate structures to modify the EV charging demand. We use a tiered approach, where we delay a given percentage of the EV load supplied by a transmission bus with locational marginal price (LMP) above one of the three thresholds shown in Table III.3.2 below.

Table III.3.2 Rate Structures

Bus LMP	% EV load delayed by 1 hour
>60 $/MWh	20%
>100 $/MWh	Additional 20% (40% total)
>600 $/MWh	Additional 20% (60% total)

These rate structures are implemented by checking the optimal power flow results after each simulation hour and comparing each transmission bus LMP value to the thresholds above. For context, the LMP is the total increase in system operating cost of supplying an additional megawatt of load at the given bus. The LMP values are also the dual variables associated with the branch flow constraints in the optimal power flow formulation.

In a grid with no transmission constraints, all bus LMPs are uniform and are set by the cost of the marginal generator. For example, in scenario 1, hour 2, there are no transmission lines operating at their limits, so the system LMP is a uniform $14.97/MWh. However, when a transmission line or transformer hits its limit, generators have to be dispatched in a less economical manner to keep the transmission line or transformer from becoming overloaded. This is called congestion and causes non-uniform LMPs at the system buses. Specifically, congestion can cause high LMP values at the bus(es) where an increase in load contributes most to increased flow on the transmission line, and the resulting generator redispatch causes more expensive generators to be used to supply the load.

In the worst case, a transmission line overload cannot be fixed by changing the outputs of the generators, and this becomes an unenforceable constraint. In reality, this overload would be corrected by shedding load, but in a planning study (such as this project), the transmission line or transformer would need to be upgraded to correct the overload. For example, in scenario 1, hour 1, there is an unenforceable constraint on the 138 kV transmission line between bus 270005 and 1200074, resulting in a 100 MW overload on the line. This overload is an example of the overloads that are calculated in the capital cost section above.

The rate structures are implemented so that the total EV load over a 24-hour period remains the same. Additionally, charging will not be delayed beyond the 24th hour (11 PM). Finally, the threshold of $60/MWh was chosen to ensure that an EV load will not be delayed the entire 24 hours.

The scenarios were analyzed, and it was determined that most of the transmission overloads for the charging-beginning-at-midnight scheme occur during two time intervals: 12 AM–4 AM and 11 AM–7 PM. For the charging-beginning-at-station-arrival scheme, the overloads also take place mostly between 5 PM and 1 AM. Thus, there are several hours in all scenarios in which all bus LMP values are below $60/MWh, ensuring that the truck charging demand will be fully met.

Conclusions

During Fiscal Year 2023, the project implemented the transportation grid co-simulation of 96 scenarios of truck charging in the Dallas–Houston megaregion. The co-simulation capability allowed for multi-dimensional comparisons of factors that impact the operating, capital, and environmental costs of the electric grid. The results of the scenario runs and the automated simulation pipeline enabled us to design rate structures and examine the cost savings. We will report the results of the rate designs in Fiscal Year 2024.

Key Publications

1. Wert, J. L., F. Safdarian, D. Wallison, J. K. Jung, Y. Liu, T. J. Overbye, and Y. Xu. 2023. "Spatiotemporal Operational Emissions Associated with Light-, Medium-, and Heavy-Duty Transportation Electrification." IEEE Transactions on Transportation Electrification. DOI: 10.1109/TTE.2023.3275050.

References

1. Environmental Protection Agency. 2022. "Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2020." Last modified on July 13, 2022. https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2020.

2. Environmental Protection Agency. 2023. Final Rule. "Control of Air Pollution from New Motor Vehicles: Heavy-Duty Engine and Vehicle Standards." Federal Register 88, no. 15 (January 24, 2023): 4324. https://www.govinfo.gov/content/pkg/FR-2023-01-24/pdf/2022-27957.pdf.

3. Xu, Yanzhi. 2022. "Technology Landscape and Future Direction for Transportation Emissions, Energy, and Health." Edited by Energy Center for Advancing Research in Transportation Emissions and Health. Texas A&M Transportation Institute. https://rosap.ntl.bts.gov/view/dot/61943.

4. Andrade, Juan, and Ross Baldick. 2017. *The Full Cost of Electricity: Estimation of Transmission Costs for New Generation*. White Paper UTEI/2016-09-2. Energy Institute, The University of Texas at Austin. https://energy.utexas.edu/sites/default/files/UTAustin_FCe_TransmissionCosts_2017.pdf

5. Hanson, G. T. 1991. "Upgrading transmission lines." *Proceedings of the 1991 IEEE Power Engineering Society Transmission and Distribution Conference*. DOI: 10.1109/TDC.1991.169599.

6. National Renewable Energy Laboratory. 2012. *Renewable Electricity Futures Study*. M. M. Hand, S. Baldwin, E. DeMeo, J. M. Reilly, T. Mai, D. Arent, G. Porro, M. Meshek, and D Sandor, eds. NREL/TP-6A20-52409. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/analysis/re-futures.html.

7. Farmer, Tara. 2023. "Cost to run power underground vs. above ground." *Homeguide*. April 5. https://homeguide.com/costs/cost-to-run-power.

8. Burlington Electric. 2020. "Chapter 4 – Transmission & Distribution." From the *City of Burlington Electric Department 2020 Integrated Resource Plan*. https://www.burlingtonelectric.com/sites/default/files/IRP2020/4_T&D.pdf.

9. Wert, J. L., F. Safdarian, D. Wallison, J. K. Jung, Y. Liu, T. J. Overbye, and Y. Xu. 2023. "Spatiotemporal Operational Emissions Associated with Light-, Medium-, and Heavy-Duty Transportation Electrification." *IEEE Transactions on Transportation Electrification*. DOI: 10.1109/TTE.2023.3275050.

Acknowledgments

We gratefully acknowledge the guidance and support of Raphael Isaac and John Terneus.

III.4 Enhancing the EVI-X National Framework to Address Emerging Questions on Charging Infrastructure Deployment (National Renewable Energy Laboratory)

Eric Wood, Principal Investigator
National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
E-mail: Eric.Wood@nrel.gov

Patrick Walsh, DOE Technology Manager
U.S. Department of Energy
E-mail: Patrick.Walsh@ee.doe.gov

Start Date: November 1, 2022 End Date: September 30, 2025
Project Funding (FY23): $360,000 DOE share: $360,000 Non-DOE share: $0

Project Introduction

U.S. climate goals for economy-wide net-zero greenhouse gas emissions by 2050 require rapid decarbonization of the light-duty vehicle fleet, and plug-in electric vehicles (PEVs) are poised to become the preferred technology for achieving this end [1]. The speed of this intended transition to PEVs is evident in actions taken by government and private industry, both in the United States and globally. New PEV sales have reached 7%–10% of the U.S. light-duty market [2]. Globally, PEV sales accounted for 14% of the light-duty market in 2022, with China and Europe at 29% and 21%, respectively [3]. A 2021 executive order targets 50% of U.S. passenger car and light truck sales as zero-emission vehicles (ZEVs) by 2030 [4], and California has established requirements for 100% light-duty ZEV sales by 2035 [5], with many states adopting or considering similar regulations [6]. These goals were set prior to passage of the landmark U.S. Bipartisan Infrastructure Law and Inflation Reduction Act, Public Law 117–169, August. 16, 2022, which provides substantial policy support through tax credits and investment grants (e.g., Electrification Coalition 2023 [7]).

Companies in the automotive industry have committed to this transition, with most companies rapidly expanding offerings [8] and many pledging to become ZEV-only manufacturers. Tesla has been a ZEV-only company since its inception in 2003; Audi, Fiat, Volvo, and Mercedes-Benz are targeting ZEV-only sales by 2030; and General Motors and Honda are targeting ZEV-only sales by 2035 and 2040, respectively [9]. The combination of policy action and industry goal-setting has led analysts to project that by 2030, PEVs could account for 48%–61% of the U.S. light-duty market [10]. This transition is unprecedented in the history of the automotive industry and will require support across multiple domains, including adequate supply chains, favorable public policy, broad consumer education, proactive grid integration, and a national charging network.

While the speed and scale of these developments is exhilarating, the implementation of these initiatives is not without risk. The co-evolution of the electric vehicle (EV) and EV supply equipment markets needs to be closely coordinated to ensure that urgent transportation decarbonization goals are met. A future where EV sales outpace the rate of charging deployments could lead to poor user experiences in regions where the network is underbuilt or non-existent. Conversely, a charging deployment that exceeds the demand for charging puts infrastructure owners/operators at risk of financial hardship through poor asset utilization, potentially increasing the cost of charging and weakening a key competitive advantage for EVs. Careful attention must be paid to maintaining the appropriate balance of the supply and demand for EV charging that promotes accelerated EV adoption while avoiding unintended consequences.

The scale of charging infrastructure investments brings greater scrutiny to the questions of deployment speed and efficiency. Lead times for utility connection requests are currently measured in months or years, depending on the size of the request and the utility involved. These "soft costs" brought on by uncertain timelines are well known to place a great burden on deployment efforts and create uncertainty for all stakeholders. To enable electric utilities to be more proactive in their planning efforts, national modeling as part of the Electric Vehicle Infrastructure suite (EVI-X) is being scaled to provide increased spatial granularity.

Ongoing federal investments in charging infrastructure bring a host of new questions to light. How aggressive should charging network companies be in attempting to future-proof new stations (e.g., station size and charging power)? With federal National Electric Vehicle Infrastructure (NEVI) formula funds targeting a national network of fast-charging stations to support consumer confidence in EVs, how many stations are likely to experience low levels of utilization, and for how long? What can be done to support these stations efficiently, with either technology or policy solutions?

All these questions can be addressed using quantitative modeling as part of the EVI-X Suite. At the national level, the National Renewable Energy Laboratory (NREL) EVI-X Modeling Suite [11] shown below in Figure III.4.1 has been the Office of Energy Efficiency and Renewable Energy's primary resource for insights on how this balance of supply and demand for charging may evolve over the next decade. Ultimately, today's market and public policy conditions present opportunities for deployment-oriented analysis to guide sound public investments.

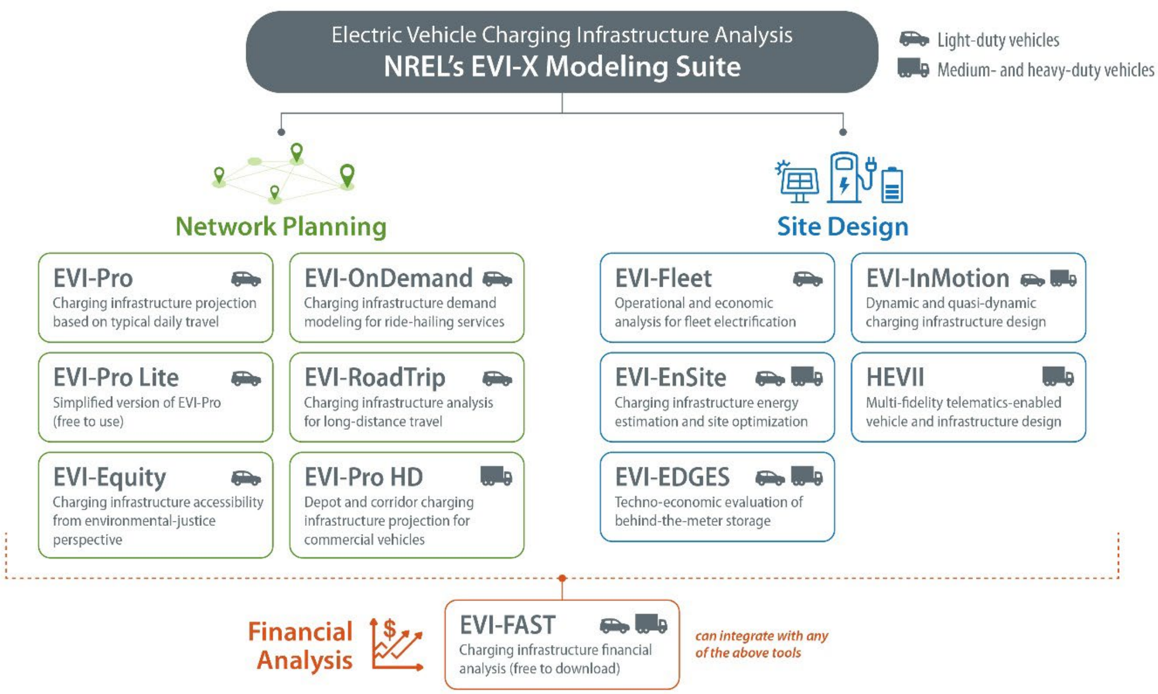


Figure III.4.1 NREL's EVI-X Modeling Suite informs the development of large-scale EV charging infrastructure deployments—from the regional, state, and national levels to site and facility operations. Source: NREL

Objectives

The goal of this project is to produce research that makes EV charging more convenient, affordable, reliable, and equitable. We aim to ensure the effective use of public funds, including sufficiently leveraging private capital. The project team is analyzing charging deployment approaches that achieve the goals of all stakeholders, as shown in Table III.4.1 below.

Table III.4.1 Charging Industry Stakeholders and Potential Incentives

Charging Stakeholder	Potential Incentives
Current and future EV drivers	Satisfy existing needs and anticipate future requirements.
Automotive manufacturers	Bolster consumer confidence in charging, making EV ownership more attractive.
Charging network providers	Balance supply and demand for charging to promote financially viable levels of utilization.
Site hosts	Make EV charging an attractive amenity for business owners and customers alike.
Electric utilities	Enable proactive planning to increase deployment efficiency and ensure grid integration.

The team's primary end-of-project goal includes enhancements to the EVI-X modeling suite that enable sophisticated financial analysis of public funding pathways, spatially granular scenario analysis that supports proactive utility planning, and large-scale network design studies inclusive of charging infrastructure supporting all vehicle weight classes. By the end of this project, modeling enhancements will have been used to produce technical reports and academic journal articles that make the financial analysis, grid planning, and network design insights available to the public. Modeling results will be shared with all relevant stakeholders, including the Joint Office of Energy and Transportation, other federal agencies, state-level officials, electric utilities, and private automotive and charging companies. These project goals are aligned with the Vehicle Technologies Office (VTO) programmatic goals aimed at enabling sector-wide transportation decarbonization.

Approach

Fiscal Year (FY) 2023 efforts under this project focus are two-pronged: (1) increase the spatial resolution of the national EVI-X framework and 2) conduct financial analysis of rural, corridor stations (potential NEVI-funded locations). While these objectives are related, they take largely independent approaches.

Increase the Spatial Resolution of the National EVI-X Framework

This task will increase the spatial resolution of the national EVI-X framework developed with VTO funding in FY 2021–2022. The outcome is expected to become a resource for electric utilities in their distribution planning processes. This task is being coordinated with VTO's EVs@Scale Consortium and the Electric Power Research Institute's EVs2Scale Initiative.

The team has developed a national origin–destination matrix for spatial disaggregation of simulated charging infrastructure and electrical load as illustrated in Figure III.4.2. This matrix is based on data licensed to NREL through the VTO Energy Efficient Mobility Systems program. INRIX is the commercial supplier of high-resolution global positioning system data for this project. The data contains hundreds of millions of real-world trips. The team has leveraged a spatial disaggregation prototype developed for California and extended the methodology to provide national coverage with geographic precision at the census tract level.

The team is scheduling a series of listening sessions with distribution planning engineers at a variety of electric utilities to better understand the load forecasting challenges at the local level. These conversations are expected to reinforce the need for high-resolution load modeling and guide the development through establishing spatial resolution guidelines that are independent of specific utility circuits. Based on industry feedback, the team will review available geographic units with national resolution and select a geography that balances the need to provide utilities with sufficient resolution while also keeping the methodology sound and defensible.

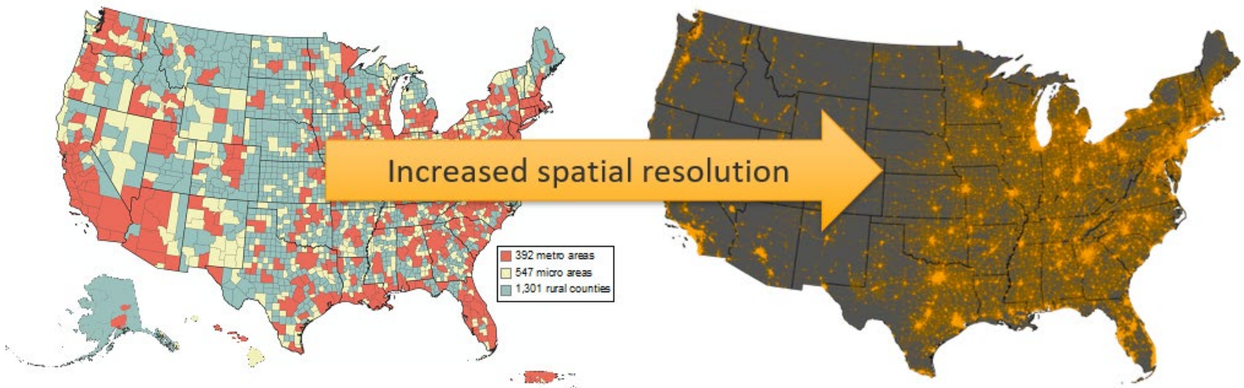


Figure III.4.2 Visual representation of increasing spatial resolution from core-based statistical area/county level to census tracts. Source: NREL

Conduct Financial Analysis of Rural Corridor Stations

This task focuses on site-level financial analysis with an emphasis on questions posed by federal investment programs. This task enhances the EVI-X national framework by coupling EVI-RoadTrip (demand estimation) and EVI-FAST (Financial Analysis Scenario Tool), as shown in Figure III.4.3, to evaluate the potential levelized cost of charging at rural, fast-charging corridor sites designed to support long-distance travel.

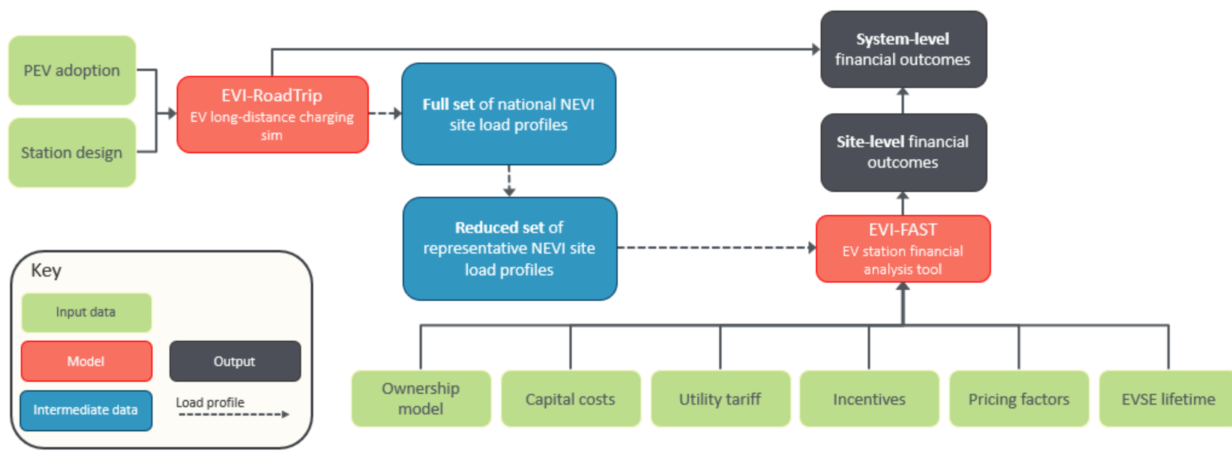


Figure III.4.3 Data pipeline for integration of EVI-RoadTrip and EVI-FAST. Source: NREL

One goal of the NEVI program is to establish the first-ever national public charging network open to all EVs. There will be sites that experience a prolonged period of low utilization as EV sales increase and drivers become more comfortable using EVs for long-distance travel. Quantitative analysis using a combination of EVI-RoadTrip and EVI-FAST is being conducted to support the federal understanding of how many sites are expected to experience a prolonged period of low utilization, where they will likely be located, and what can be done to mitigate federal subsidies for operating expenses. This subtask will produce guidance on sustainable support mechanisms for underutilized stations that are necessary for complete and equitable public charging access across the United States.

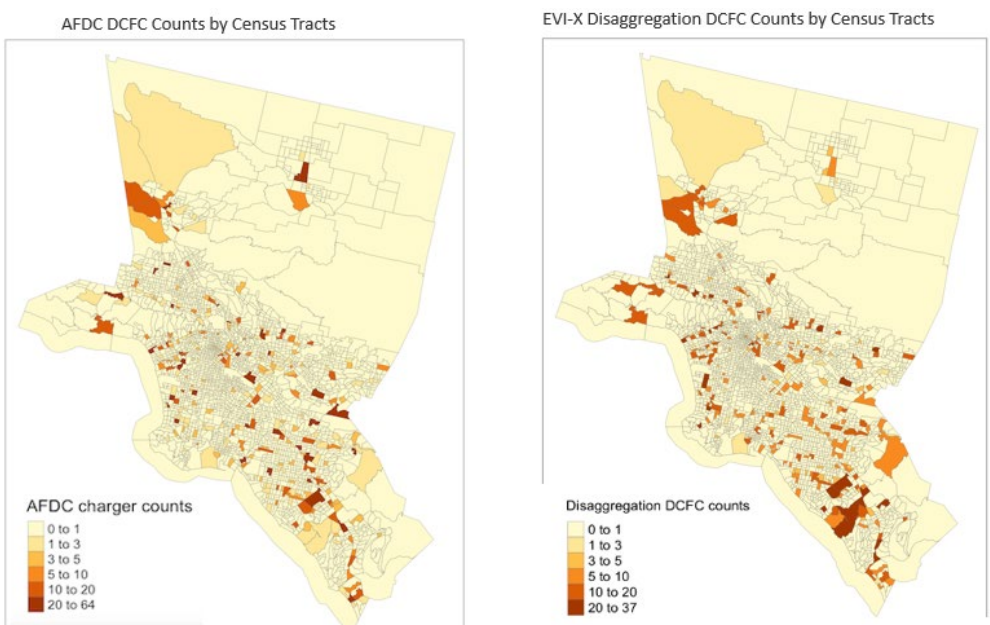
Much attention has been paid to the need to "future-proof" sites—that is, constructing sites today that anticipate increased demands for charging over time and increased vehicle-level capabilities (e.g., increased direct current [DC] charging acceptance rates). However, there is limited analysis that objectively trades off the costs and benefits of intentionally over-designing sites in anticipation of future needs. The concept is intuitive in that it limits the frequency of new construction, but the push to future-proof tends to ignore the risk posed by operating and maintaining charging equipment in advance of its actual use. This task is exploring case studies that leverage discounted cash flow analysis to identify conditions in which future-proofing ultimately provides net benefits, particularly to EV drivers, the station owner/operator, and applicable public funding agencies.

Results

Increase the Spatial Resolution of the National EVI-X Framework

The EVI-X national framework provides infrastructure estimates at the resolution of core-based statistical areas (CBSAs) or counties. EVI-X is being enhanced using high-resolution telematics data to disaggregate infrastructure demand within each CBSA/county. A likely adopter model has been applied to each zone within the national framework to dissolve EV home locations at the tract level. This spatial disaggregation includes estimates of those with and without access to residential charging, a key variable for estimating charging demand away from home. Utilities can use these estimates to anticipate demand on distribution networks and make proactive investments to ensure reliable service to customers.

A similar disaggregation was conducted for public DC fast charging (DCFC) in southern California, as shown in Figure III.4.4. NREL modeling indicates that 90% of the 2030-simulated DCFC demand nationally will be within urban areas. National telematics data from millions of devices (as licensed from INRIX) is being used to disaggregate public charging demand (including community-based fast charging). Figure III.4.4 shows a comparison of the public DCFC network in Los Angeles County by census tract as observed by the DOE Alternative Fuels Data Center (AFDC) Station Locator (as of early 2023) and a modeled disaggregation of the same area. Visually, a high degree of correlation can be observed between station locations. Similarly, charging while at work (public and private access) is expected to be the dominant non-residential use case for Level 2 charging. Longitudinal origin–destination data from the census is being used to disaggregate simulated demand to the tract level for all U.S. CBSAs.



(a) (b)

Figure III.4.4 (a) **Actual public DCFC locations compared to** (b) **a modeled disaggregation of the 2023 network for Los Angeles County. Source NREL**

Conduct Financial Analysis of Rural Corridor Stations

EVI-X national simulation results suggest 18,000 DC ports could be necessary outside urban areas by 2030 (about 10% of the simulated national fast-charging network). Of these, approximately half of rural corridor stations are estimated to experience low levels of utilization through 2030 (based specifically on results from EVI-RoadTrip; a map of simulated demand is included below in Figure III.4.5). Despite forecasts for low annual utilization, these rural corridor DCFC stations will be necessary to support national long-distance trips during peak travel seasons and around holidays.

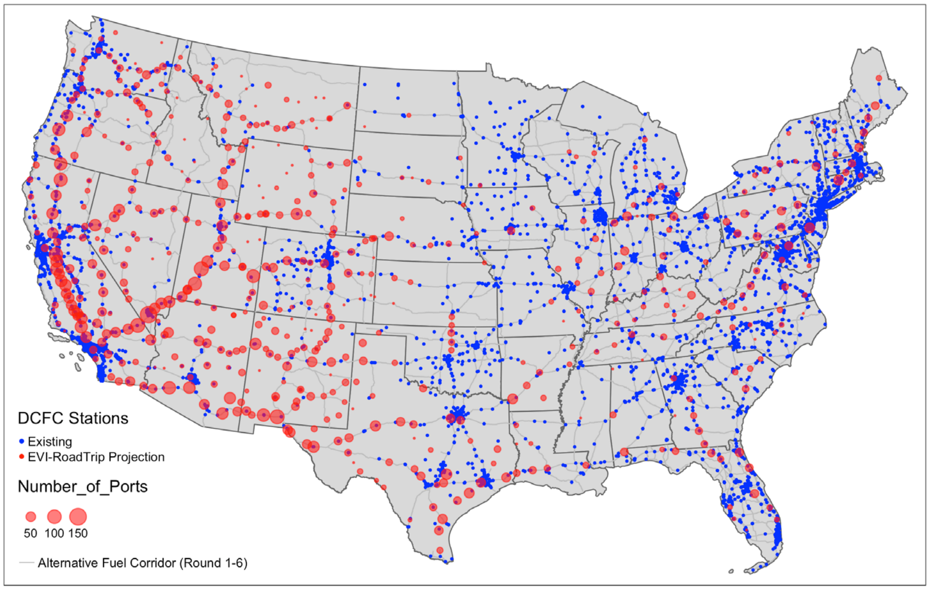


Figure III.4.5 Simulated 2030 DCFC demand from EVI-RoadTrip, contrasted with existing station locations. Source: NREL

Conclusions

Significant investments are being made in U.S. EV charging infrastructure. Third-party estimates suggest that more than $5 billion in private investment was committed domestically in the first quarter of 2023 alone. Efficient deployment of infrastructure is aided by sophisticated planning tools that are independently developed and vetted.

This project makes contributions in two specific areas: (1) increasing spatial resolution of national modeling using large telematics datasets to support granular utility planning and (2) evaluating levelized cost of charging by integrating spatially explicit demand estimates with detailed financial analysis targeted at potential NEVI-locations. These thrusts have laid the foundation for a national utility planning tool with distribution-level resolution and estimated that as many as half of rural fast-charge stations are likely to experience low utilization through 2030. Multiple stakeholder groups have contributed to the overall research scope, including automotive manufacturers, charging networks, and electric utilities.

This work is scheduled to be refined in FY 2024 by updating key financial analysis parameters, increasing the spatial resolution of demand forecasting, and continuing to engage with industry stakeholders and adapt the project plan accordingly.

Key Publications

1. Wood, E., B. Borlaug, M. Moniot, D-Y Lee, Y. Ge, F. Yang, and Z. Liu. 2023. "The 2030 National Charging Network: Estimating U.S. Light-Duty Demand for Electric Vehicle Charging Infrastructure." NREL Technical Report 85654, June. https://www.nrel.gov/docs/fy23osti/85654.pdf.

2. Wood, E., B. Borlaug, D-Y Lee, Y. Ge, and F. Yang. 2023. "Enhancing the EVI-X National Framework to Address Emerging Questions on Charging Infrastructure Deployment." Presented at the 2023 Vehicle Technologies Office Annual Merit Review. https://www.nrel.gov/docs/fy24osti/86030.pdf.

3. Wood, E., D-Y Lee, L. Spath-Luhring, B. Borlaug, M. St. Louis-Sanchez, Y. Ge, and F. Yang. 2023. "EVI-X Updates and National Charging Assessment Report." Presented at the 2023 Vehicle Technologies Office Annual Merit Review, https://www.nrel.gov/docs/fy24osti/86417.pdf.

References

1. Berube, Michael, Andrew Wishnia, Karl Simon, Alexis Pelosi, Matteo Muratori, Tatjana Kunz, Aaron Hula, and Michael Freedberg. 2023. *The U.S. National Blueprint for Transportation Decarbonization*. DOE/EE-2674. Washington, D.C.: U.S. Department of Energy. https://www.energy.gov/sites/default/files/2023-01/the-us-national-blueprint-for-transportation-decarbonization.pdf.

2. Argonne National Laboratory. 2023. "Light Duty Electric Drive Vehicles Monthly Sales Updates." https://www.anl.gov/esia/light-duty-electric-drive-vehicles-monthly-sales-updates.

3. International Energy Agency (IEA). 2023. *Global EV Outlook 2023: Catching up with climate ambitions*. Paris, France: IEA. https://iea.blob.core.windows.net/assets/dacf14d2-eabc-498a-8263-9f97fd5dc327/GEVO2023.pdf.

4. Executive Office of the President. 2021. "Executive Order 14037: Strengthening American Leadership in Clean Cars and Trucks." Federal Register 86 FR 43583, August 5. https://www.federalregister.gov/documents/2021/08/10/2021-17121/strengthening-american-leadership-in-clean-cars-and-trucks.

5. California Air Resources Board. 2022. "California moves to accelerate to 100% new zero-emission vehicle sales by 2035." News release 22-30, August 25. https://ww2.arb.ca.gov/news/california-moves-accelerate-100-new-zero-emission-vehicle-sales-2035.

6. Khatib, Moe. 2022. "Advanced Clean Cars Goes National." *EV Hub*. October 4. https://www.atlasevhub.com/weekly-digest/advanced-clean-cars-goes-national/.

7. Electrification Coalition, 1111 19th Street, NW, Suite 406 Washington, DC 20036 https://electrificationcoalition.org/electric-freight-funding/

8. Bartlett, J. S., and B. Preston. 2023. "Automakers Are Adding Electric Vehicles to Their Lineups. Here's What's Coming." *Consumer Reports*. March 10. https://www.consumerreports.org/cars/hybrids-evs/why-electric-cars-may-soon-flood-the-us-market-a9006292675/.

9. Bloomberg New Energy Finance. 2022. "Zero-Emission Vehicles Factbook, A BloombergNEF special report prepared for COP27." https://assets.bbhub.io/professional/sites/24/2022-COP27-ZEV-Transition_Factbook.pdf

10. Slowik, Peter, Stephanie Searle, Hussein Basma, Josh Miller, Yuanrong Zhou, Felipe Rodriguez, Claire Buysse, Sara Kelly, Ran Minjares, and Logan Pierce. 2023. "Analyzing the Impact of the Inflation Reduction Act on Electric Vehicle Uptake in the United States." ICCT White Paper. https://theicct.org/wp-content/uploads/2023/01/ira-impact-evs-us-jan23-2.pdf.

11. NREL. 2023. "EVI-X Modeling Suite of Electric Vehicle Charging Infrastructure Analysis Tools." https://www.nrel.gov/transportation/evi-x.html.

IV Energy and Emissions Modeling

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

Ram Vijayagopal, Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave.
Lemont, IL 60439
Email: rvijayagopal@anl.gov

Ehsan Islam, Co-Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave.
Lemont, IL 60439
Email: eislam@anl.gov

Daniela Nieto Prada, Co-Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave.
Lemont, IL 60439
Email: dnprada@anl.gov

Charbel Mansour, Co-Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave.
Lemont, IL 60439
Email: cmansour@anl.gov

Aymeric Rousseau, Co-Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave.
Lemont, IL 60439
E-mail: arousseau@anl.gov

Patrick Walsh, Technology Manager
U.S. Department of Energy
E-mail: Patrick.Walsh@ee.doe.gov

Start Date: October 1, 2022	End Date: September 30, 2025	
Project Funding (FY23): $480,000	DOE share: $480,000	Non-DOE share: $0
Total Expected Project Funding: $1,480,000	DOE share: $1,480,000	Non-DOE share: $0

Project Introduction

Vehicle simulation is a reliable way to predict the cost and energy consumption benefits of technology changes in automotive applications. This work relies on Autonomie [1], a simulation tool developed by Argonne National Laboratory (ANL) and funded by the U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO), to quantify the energy consumption and cost of technologies. This work also uses the TechScape (Technology landScape) tool developed by ANL to quantify the technoeconomic benefits and emissions of advanced vehicle technologies [2]. The project integrates VTO-sourced data with component-level technology performance and cost to generate vehicle-level metadata based on U.S. standard driving cycles. Autonomie vehicle models and results are used to support several activities within VTO—life cycle analysis (LCA), economic impact analysis, market penetration analysis, and development of individual component technology targets—as well as activities outside of VTO.

Objectives

The main goals of this project are 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 and cost as well as 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 the tasks shown in Table IV.1.1.

Table IV.1.1 ANL Project Tasks

#	Tasks	Status
1	Quantify benefits of VTO-funded technologies for light-duty vehicles	Complete
2	Quantify benefits of VTO-funded technologies for medium- and heavy-duty vehicles	Complete
3	Make improvements to TechScape	Complete

Task 1 was to quantify the energy consumption and cost of several types of light-duty vehicles. The scope of this task extended from small passenger cars in light-duty segments to pickup trucks. Task 2 was to quantify the energy consumption and cost of several types of medium- and heavy-duty vehicles, spanning across large, long-haul trucks in heavy-duty segments. Several vehicles were identified to represent the large variety of vehicles in the light-, medium-, and heavy-duty segments. This study examined the differences in vehicle requirements and use cases in 10 types of light-duty vehicles and more than 20 types of medium- and heavy-duty trucks. The assumptions used for defining these vehicles were based on inputs provided by transportation decarbonization analyses conducted by VTO and the DOE Hydrogen and Fuel Cell Technologies Office [3]. This work used updated powertrain and sizing assumptions based on these inputs. As noted above, the project used Autonomie for simulation and TechScape for technoeconomic analysis. TechScape provides a user interface that enables users to examine the sensitivity of the total cost of ownership (TCO) and LCA of a vehicle to its component efficiency and cost assumptions.

Task 3 covers various development improvements in TechScape. This task included migrating TechScape from Excel to Python for the cost, energy, and LCA modules. Task 3 also includes development of a material analysis module (with linkages to the ANL BatPaC tool [4]), an LCA module (with linkages to GREET [5]), and a fleet analysis module that would enable users to compute the energy, emissions, materials, and costs for overall fleets and national impact.

Results

The results of the Fiscal Year (FY) 2023 analysis activities are covered in this section and, as in the Approach section, follow the task outline.

The main output of Tasks 1 and 2 is a report that covers the assumptions, vehicle sizing, and simulation results of both light-duty and medium- to heavy-duty vehicles. The databases accompanying the report provide the details of all vehicle-level assumptions, fuel economy observed on regulatory cycles, and the estimated manufacturing cost and operational cost of each vehicle [6]. The FY 2023 report and databases are accessible on the ANL website [7].

This dataset forms the basis of LCA and other DOE-funded market penetration predictions. The Annual Technology Baseline project by the National Renewable Energy Laboratory [8] also relies on vehicle simulation results from this work.

The FY 2023 report presents a quick overview of the results available in the database. Vehicles and technologies for future timeframes were modeled in this work. Two potential scenarios for technology progress were examined: (1) a business-as-usual scenario (low) and (2) a scenario based on 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 the years to come because of accompanying technological advances. In addition to the component requirements, the database also provides information on projected vehicle-level cost, weight, energy consumption, and cost of driving and ownership for various powertrains, as well as different emission metrics. This information helps in understanding when advanced powertrains might achieve functional and economic parity with competing choices.

Task 1. Quantifying Vehicle Energy Consumption and Cost Estimation for Light-Duty Vehicles

In 2023, the full combined report for the light-duty vehicle simulations was published as the final deliverable. The report provides different analytics on the key metrics across the different vehicle powertrains (conventional, hybrids, plug-in hybrids, battery electric vehicles [BEVs]). Figure IV.1.1 shows the cost parity of BEVs for passenger cars (small sport utility vehicle [SUV] class). The cost parity is against the conventional spark injection (SI) turbocharged vehicle of the corresponding analysis year. For small SUVs, if current technology progress trends (low-technology scenario) continue, BEVs with an all-electric range of 300 miles or less will become cost-competitive with conventional powertrains around 2035. In the high-technology scenario (VTO targets), BEVs become cost-competitive an average of ten years earlier, thus significantly accelerating their market adoption.

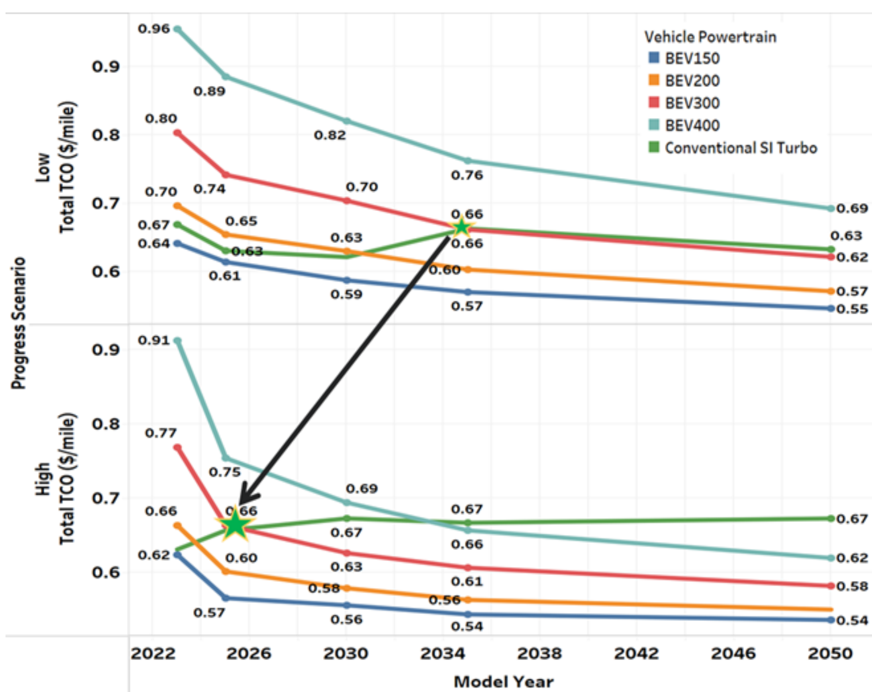


Figure IV.1.1 TCO comparison across powertrains for small SUVs. Source: ANL

Task 2. Quantifying Vehicle Energy Consumption and Cost Estimation for Medium- and Heavy-Duty Vehicles

Figure IV.1.2 shows the weight, cost, energy consumption, and TCO of hybrid, fuel cell hybrid electric vehicles (FCHEV), and electric vehicles as a function of the corresponding values of conventional diesel trucks. This analysis projects a gradual reduction of the cost and weight penalties for all powertrains. In fact, this study finds that electric and fuel cell trucks will be able to compete with diesel trucks, even in this segment, if the high level of technology progress assumed in this study is met. 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. Fuel cell vehicles are expected to achieve TCO parity by 2030, 10 years earlier than the low-technology scenario.

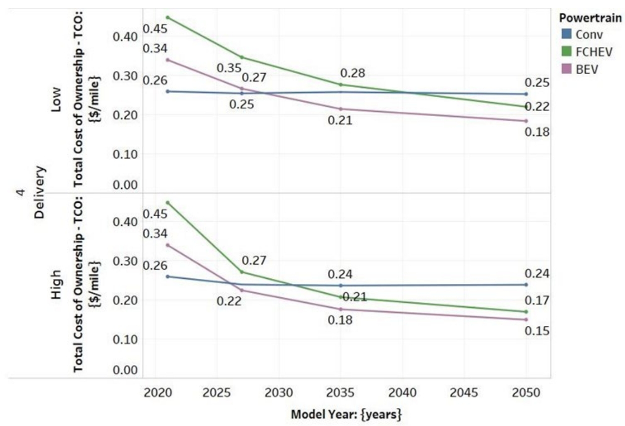


Figure IV.1.2 Evolution of vehicle cost, weight, and energy consumption for long-haul trucks that use advanced powertrains. All percentages are computed based on the conventional truck parameters for that year. Source: ANL

Figure IV.1.3 examines the impact of technological progress on vehicle weight, vehicle cost, and TCO for Class 6 box FCEV trucks over time. In both high- and low-technology scenarios, advanced powertrains initially incur cost and weight penalties compared to the conventional baseline in 2023 and 2025. However, several advanced powertrains achieve cost parity in terms of initial cost by 2035 and 2050 and surpass conventional vehicles in terms of reduced ownership cost, becoming more economical as early as 2030. In the low-technology scenario, some advanced powertrains can achieve cost parity in both initial and ownership costs by 2050. These results underscore the need for aggressive technological improvements for the successful introduction of advanced powertrains in the medium- and heavy-duty segments.

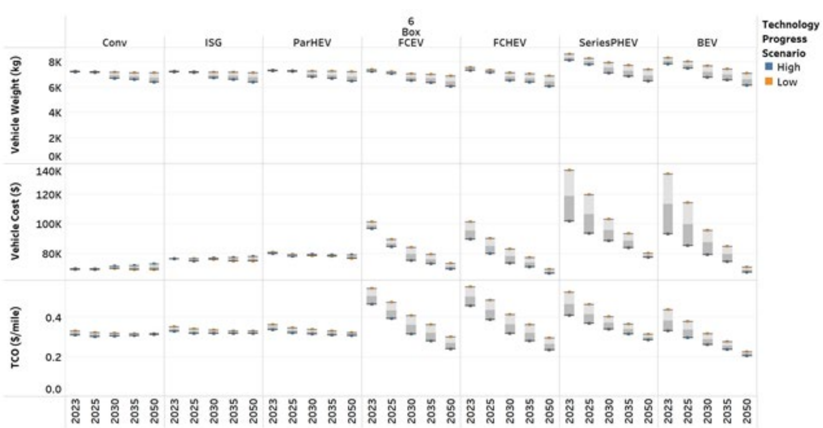


Figure IV.1.3 Impact of technology progress on weight, cost, and TCO of Class 6 box trucks. Source: ANL

Figure IV.1.4 shows a more thorough examination of the Class 6 BEV truck trends observed in the preceding figure, providing an in-depth exploration of the evolution of battery energy requirements, electricity consumption, battery costs, and vehicle prices over time. Notably, under conditions of high technology progress, we estimate a ~26% reduction in battery requirements by 2050. This reduction in component sizes leads to a significant decrease in vehicle weight, resulting in a reduction in energy consumption of about 35%. Moreover, there is a considerable decrease in battery costs, subsequently translating into a lower vehicle manufacturer's suggested retail price. In summary, the research funded by VTO plays a pivotal role in achieving significant reductions in both energy consumption and vehicle costs.

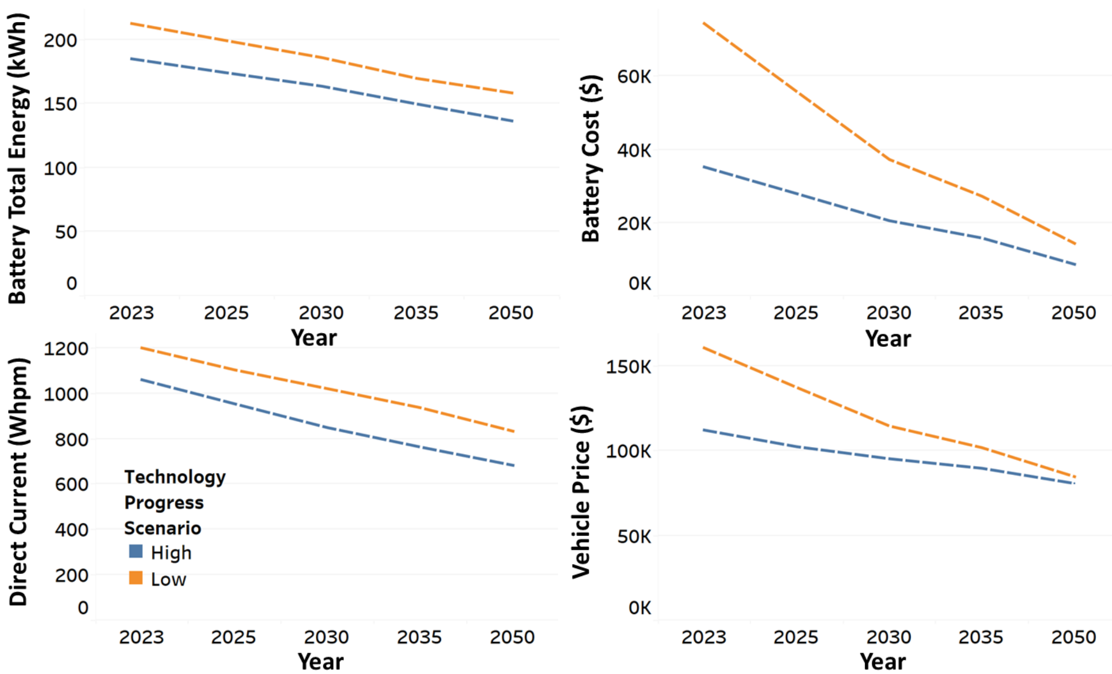


Figure IV.1.4 Evolution of battery energy, energy consumption, battery costs, and vehicle prices for Class 6 BEV trucks over time. Source: ANL

Task 3. TechScape Improvements

In FY 2023, the TechScape task achieved several objectives. The project team focused on TechScape core development and involved migrating key modules from Excel to Python, establishing linkages for materials analysis, and updating LCA pathways. This effort also involved introducing a fleet analysis module for comprehensive fleet sales- and stock-level assessments. The team also worked on TechScape Web development, enhancing backend databases, creating interactive data visualization tools via Tableau, and launching the TechScape Web application on the ANL Vehicle and Mobility Systems website [9]. Figure IV.1.5 shows a sample analysis of TCO breakdown of Model Year 2023 vehicles across different powertrains through TechScape Web. [10]

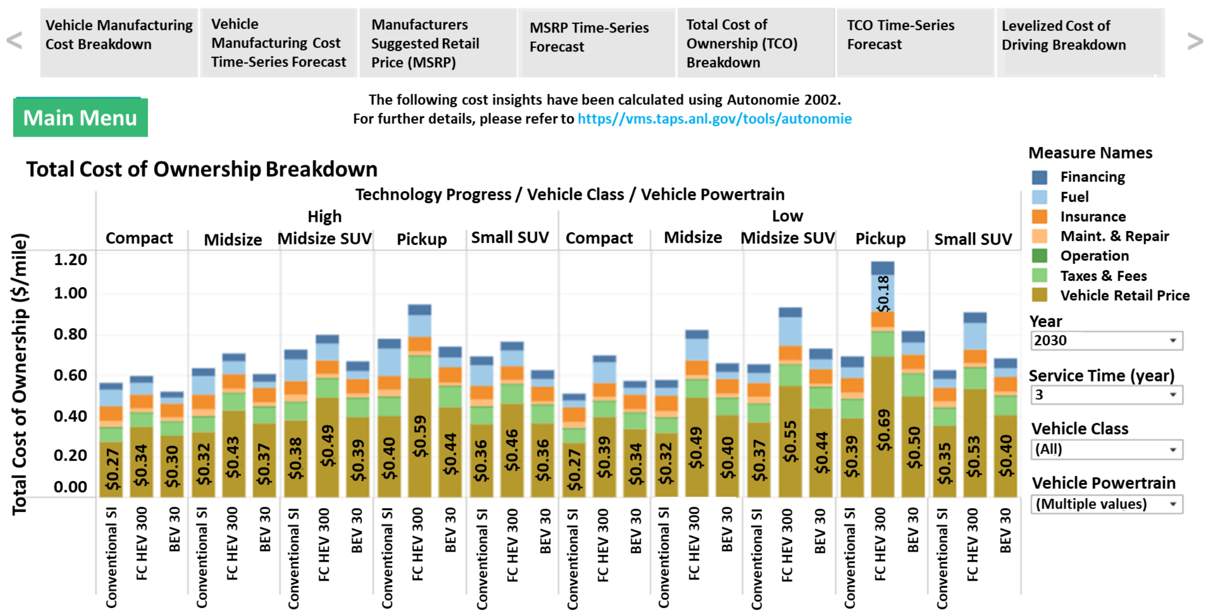


Figure IV.1.5 Sample analysis presented through TechScape Web interface. Source: ANL

Conclusions

The team has completed all the tasks planned for FY 2023. This work has resulted in a detailed report and multiple conference and journal publications. The final report covers the energy consumption, performance, and cost of light-, medium-, and heavy-duty vehicles [5]. The simulation and data analysis support that was provided for cradle-to-grave analysis activities has helped various technical teams in determining the appropriate technology development goals.

Key Publications

1. Islam, E., D. Nieto, et al. 2023. Detailed Simulation Study to Evaluate Future Transportation Decarbonization Potential. ANL/TAPS-23/3. Forthcoming.

2. Islam, Ehsan, and Ram Vijayagopal. 2023. "Impact of U.S. DOE Vehicle Technologies Progress in Technoeconomic Feasibility of Future Electrified Vehicles." Presented at the 36th International Electric Vehicle Symposium and Exhibition, Sacramento, CA.

3. Mansour, C., O. Sahin, N. Zuniga-Garcia, R. Vijayagopal, and H. Borhan. 2023. "Assessment of Advanced Long-Haul Truck Powertrains: Comparative Study of Consumption, Emissions, and Cost with Diesel Trucks." Paper number FWC2023-PPE-026. Presented at FISITA 2023 World Congress, Barcelona.

4. Mansour, C., E. Sabri Islam, R. Vijayagopal, S. Pagerit, and A. Rousseau. 2023. "Assessing the Potential Consumption and Cost Benefits of Next-Generation Technologies for Medium- and Heavy-Duty Vehicles: A Vehicle-Level Perspective." Presented at 2023 IEEE Vehicular Power and Propulsion Conference, Milan.

5. Vijayagopal, Ram, and Ehsan Islam. 2023. "Impact of technology progress and design choices on the techno economic feasibility of electric vehicles." Presented at the 36th International Electric Vehicle Symposium and Exhibition, Sacramento, CA.

References

1. ANL. 2023. "Autonomie software." https://vms.taps.anl.gov/tools/autonomie/.

2. ANL. 2023. “TechScape software.” https://vms.taps.anl.gov/tools/techscape/.
3. VTO. 2021. *Analysis Program Annual Progress Report (FY2020)*. https://doi.org/10.2172/1826267.
4. ANL. n.d. “BatPaC – A Spreadsheet Tool to Design a Lithium Ion Battery and Estimate Its Production Cost.” Accessed 2023. https://www.anl.gov/cse/batpac-model-software.
5. ANL. 2023. “R&D GREET Model.” Accessed 2023. https://greet.anl.gov/.
6. Islam, Ehsan Sabri, Ram Vijayagopal, and Aymeric Rousseau. 2022. *A Comprehensive Simulation Study to Evaluate Future Vehicle Energy and Cost Reduction Potential*. ANL/ESD-22/6. https://anl.app.box.com/s/qc3nov3w25qmxs20b2m2wmru0gadp83z.
7. Islam, Ehsan Sabri, Daniela Nieto Prada, Ram Vijayagopal, Charbel Mansour, Paul Phillips, Namdoo Kim, Michel Alhajjar, Aymeric Rousseau. 2023. “Detailed Simulation Study to Evaluate Future Transportation Decarbonization Potential.” Report to the U.S. Department of Energy, Contract ANL/TAPS-23/3. https://vms.taps.anl.gov/research-highlights/u-s-doe-vto-hfto-r-d-benefits/.
8. National Renewable Energy Laboratory. 2020. “Annual Technology Baseline.” https://atb.nrel.gov/.
9. ANL. n.d. “TechScape Web 2023.” Accessed 2023. https://vms.taps.anl.gov/data/techscape-web-2023/.
10. National Renewable Energy Laboratory. 2022. “Fleet DNA: Commercial Fleet Vehicle Operating Data.” www.nrel.gov/fleetdna.

IV.2 Holistic Modeling of Future Transportation Energy Use and Emissions: Transportation Energy and Mobility Pathway Options (TEMPO) Model (National Renewable Energy Laboratory)

Paige Jadun, Principal Investigator
National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
E-mail: Paige.Jadun@nrel.gov

Matteo Muratori, Principal Investigator
National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
E-mail: Matteo.Muratori@nrel.gov

Patrick Walsh, Technology Manager
U.S. Department of Energy
E-mail: Patrick.Walsh@ee.doe.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: November 14, 2022 End Date: December 31, 2025
Project Funding (FY23): $500,000 DOE share: $500,000 Non-DOE share: $0

Project Introduction

As the transportation sector continues to evolve and new technologies and travel solutions emerge to enable decarbonization, there remains substantial uncertainty about the future of mobility and the pathways necessary to achieve equitable and sustainable transportation sector targets [1], [2]. Transportation sector models can help to address this uncertainty by projecting ranges of potential futures for consumer travel behavior, the movement of goods, technology adoption, and the impacts of these factors on the transportation energy system.

This project supports and enhances the Transportation Energy and Mobility Pathway Options™ (TEMPO) model, a comprehensive model of the entire U.S. transportation sector [3]. TEMPO evaluates long-term scenarios of travel demand, energy consumption, and greenhouse gas emissions across all passenger and freight travel modes. TEMPO models passenger and freight travel demands, mode choice, and technology and fuel choices across an array of market segments encompassing different socioeconomic categories (for passenger modes) and use cases (for freight modes). TEMPO considers factors such as technology cost, infrastructure availability, and incentives. It also models the energy consumption and greenhouse gas emissions that result from these factors, allowing the user to evaluate the impact of different market conditions and policy levers on future transportation sector pathways. As part of this project, several key updates were made to TEMPO to improve its ability to model the current policy landscape and potential scenarios of transportation sector evolution.

Objectives

This project has two main objectives:

- Provide continued support and maintenance for the TEMPO model, enabling key model enhancements that support conducting timely and relevant transportation sector scenario analyses.
- Provide support for the U.S. Department of Energy (DOE) to answer high-urgency requests to support decision-making.

To reach these objectives, the following milestones were identified for Fiscal Year (FY) 2023:

- Expand the TEMPO steering committee (a group of DOE and external experts informing and guiding model development and prioritizing applications) to include members with expertise on environmental justice and equity.
- Identify key model enhancement needs and work toward implementing those in the model.
- Report on model upkeep and development activities.
- Identify key model enhancement milestones, in partnership with DOE, and document (paper or report) a key TEMPO model enhancement and its resulting insights.

As of November 2023, the first three of the FY 2023 project objectives have been completed, while the fourth has been scoped (a publication on modeling the impacts of the 2022 Inflation Reduction Act [IRA] for the U.S. transportation sector), and the paper's completion is expected by the end of 2023 (with DOE approval). In addition, the TEMPO model has been used to support several projects and efforts, including DECARB [4], EMF-37 [5], and several products and publications (listed below) include TEMPO results, in part thanks to the support of model development and maintenance made possible by this project:

- The U.S. National Blueprint for Transportation Decarbonization [6]
- "Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States: Results From and Methods Behind Bottom-Up Simulations of County-Specific Household Electric Vehicle Charging Load (Hourly 8760) Profiles Projected Through 2050 for Differentiated Household and Vehicle Types" [7], which was used to benchmark the Electric Power Research Institute's (EPRI's) EVs2Scale2030 efforts
- "Electric Vehicle Managed Charging: Forward-Looking Estimates of Bulk Power System Value" [8]
- "Renewable Energy and Efficiency Technologies in Scenarios of U.S. Decarbonization in Two Types of Models: Comparison of GCAM [Global Change Assessment Model] Modeling and Sector-Specific Modeling" [9]
- "Exploring decarbonization pathways for USA passenger and freight mobility," published in 2023 [10]

Approach

Regarding our first objective, expanding TEMPO's steering committee, Dr. Benjamin Sovacool, an expert in environmental justice and climate change, accepted our invitation to join the TEMPO steering committee. A steering committee meeting was held to further discuss ways in which the TEMPO model can be leveraged toward environmental justice and equity questions.

Priorities for TEMPO enhancements were determined in consultation with DOE. The following enhancements were identified as priorities in FY 2023:

- Enhancing TEMPO's capability to model exogenously specified light-duty vehicle (LDV) adoption scenarios (i.e., technology-specific adoption targets) by enabling the model to endogenously allocate adoption across vehicle classes based on market heterogeneities and preferences. For example, when given a scenario with exogenously specified battery electric vehicle (EV) sales targets, this enhancement allows the model to choose the vehicle classes in which these EVs are adopted (compact, midsize, pickup, or sports utility vehicle [SUV]), based on consumer preferences for EVs within these classes.

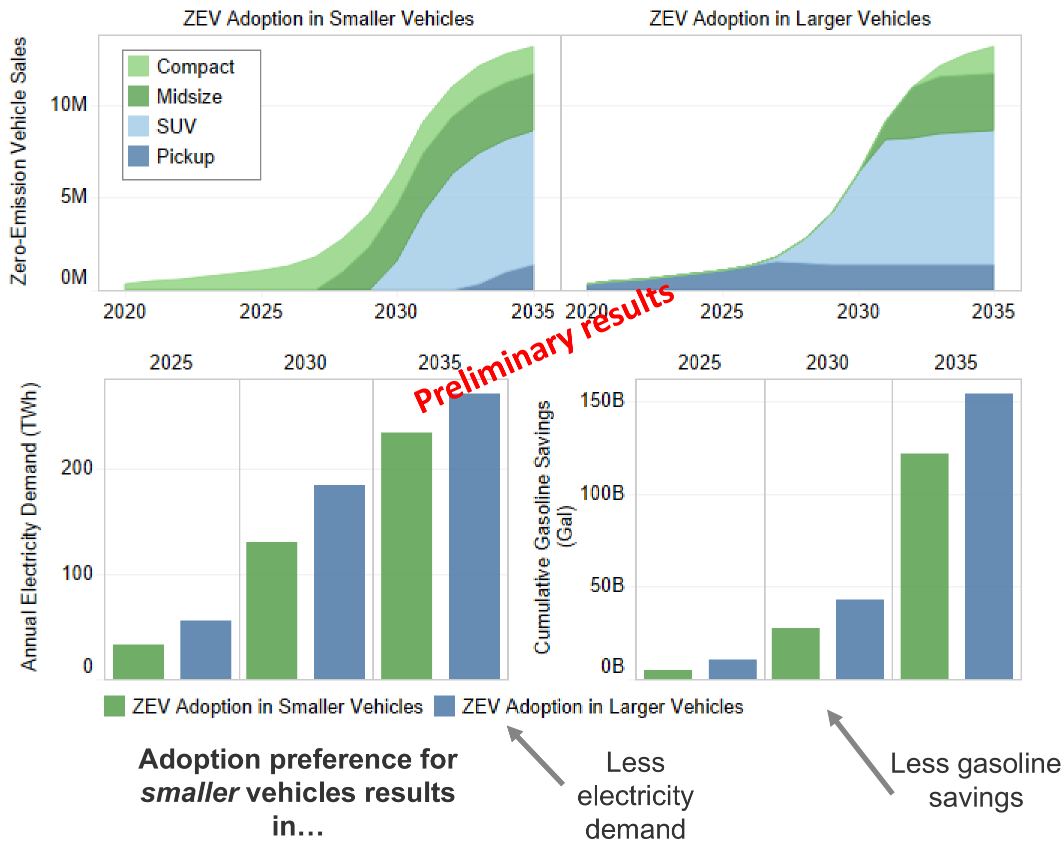
- Enhancing TEMPO's ability to model the IRA's impacts on the transportation sector, including the Clean Vehicle Tax Credit (30D), the Commercial Clean Vehicle Tax Credit (45W), and the Advanced Manufacturing Production Tax Credit (45X). These enhancements involved information-gathering; consulting with steering committee members; and estimating realized tax credits based on projected vehicle costs, battery costs, and other factors.
- Implementing near-term constraints on medium- and heavy-duty vehicle (MHDV) adoption due to battery manufacturing capacity, charging infrastructure availability, and other potential supply chain issues.
- Updating TEMPO's charging profile module, which models LDVs' hourly charging behavior, to consider hourly charging infrastructure availability (residential, workplace, or public), and expanding this module to consider MHDV charging behavior.
- Expanding TEMPO's representation of passenger modes of travel, including biking and walking, and updating TEMPO's mode choice calibration to accurately represent these alternatives.

Progress has been made on all model enhancements, with preliminary results available for the first and second enhancements. The second model enhancement, modeling the impacts of the IRA, is being developed as a National Renewable Energy Laboratory (NREL) report, with updated results expected at the end of the 2023.

Results

We first present preliminary results of the first model enhancement: Expanding TEMPO's capabilities to model exogenously specified LDV adoption scenarios, based on consumer preferences. Previously, when modeling an LDV adoption scenario (such as one specifying 50% EV sales by 2030), the TEMPO model lacked the ability to endogenously choose the vehicle classes and consumer types/locations in which EV adoption was likely to occur (e.g., relative proportions of sales across compact cars, midsize cars, pickups, and SUVs). This gap limited the insights that could be provided. It was addressed by implementing an optimization algorithm, which uses TEMPO's endogenously estimated utility of different vehicle classes and technologies (such as EVs) across different household bins (including household size, income level, and urbanicity) to determine priorities for EV adoption while complying with the sales target. Consumer adoption of different vehicle technologies and classes is estimated endogenously in TEMPO as a function of vehicle cost, infrastructure availability, and time intensity (which all vary for different household bins in TEMPO). Estimates are calibrated to historical data.

Figure IV.2.1 shows the results of this model improvement and its impacts on scenario analysis. The left side of Figure IV.2.1 shows a scenario in which an exogenous EV sales target (50% sales by 2030 and 100% by 2035) is met based on endogenous preferences for vehicle classes. The right side of Figure IV.2.1 shows a scenario in which EVs are adopted uniformly across all vehicle classes, in proportion to each class's share of the market. The results show that with endogenous class-based adoption preferences, EVs are allocated disproportionately to smaller vehicles (compact and midsize) in the early years, gaining market share in SUVs and pickups only in the late 2020s. Consumer preference for compact EVs, in particular, is disproportionate to their market share. This is primarily due to their lower cost, as larger vehicles require larger batteries to achieve equivalent ranges. Preferences for smaller EVs in the left-hand scenario have implications for energy consumption, as smaller vehicles consume less energy (both electricity and gas). The relatively high percentage of small vehicles adopted results in approximately 10% reduced electricity demand in 2035 and 25% reduced gasoline savings (vs. a scenario in which large EVs are adopted at a rate that reflects large vehicle market share). This finding highlights the importance of considering vehicle technology characteristics when evaluating the impacts of sector-level policies.



ZEV = zero-emission vehicle

Figure IV.2.1 Results of expanded LDV exogenous adoption modeling capabilities [1]

We next present preliminary results for the second model enhancement: Improving TEMPO's ability to model the impacts of the IRA. The IRA provides a wide range of incentives targeted at decarbonizing the transportation sector, including tax credits toward the purchase of zero-emission vehicles (ZEVs) (both new and used), the production of low-carbon transportation fuels, buildout of ZEV refueling infrastructure, and manufacture of EV components and batteries, among others. Surveying literature and consulting with modelers and policy experts helped the TEMPO team identify key elements to capture in TEMPO and strategies for policy implementation in the model. In the current implementation, the TEMPO team has included tax credits for personal clean vehicles, commercial vehicles, clean electricity and hydrogen production, and battery manufacturing. This project offered an opportunity for multiple expert discussions and model intercomparison around IRA implementation in transportation and economy-wide models to help advance the understanding of key IRA modeling components and enable more coordination across analysis efforts within and outside DOE.

We focused primarily on the update to consider domestic battery capacity constraints and their implications for EV adoption scenarios with and without the IRA. Domestic battery manufacturing capacity, which is estimated from the U.S. Environmental Protection Agency's OMEGA model [11], is relevant to the tax credit amounts received by LDVs under provision 30D. Efforts are under way to also consider international capacity when considering constraints on sector-wide production of EVs. Our results, as illustrated in Figure IV.2.2, show that under high technology progress assumptions (rapid improvements in battery cost and energy density), domestic battery supply may be a constraining factor on EV adoption in the near term, particularly for non-LDV modes. This constraint is particularly relevant in a scenario that considers the impact of IRA tax credits, which substantially increase near-term demand, particularly for MHDVs. However, in the longer term (beyond 2025 to 2030), these supply chain constraints do not appear to be binding for EV adoption in this scenario. A full consideration of the IRA's impacts on the MHDV and LDV modes, including the impacts of critical materials requirements and supply chain constraints, will be presented in a forthcoming report.

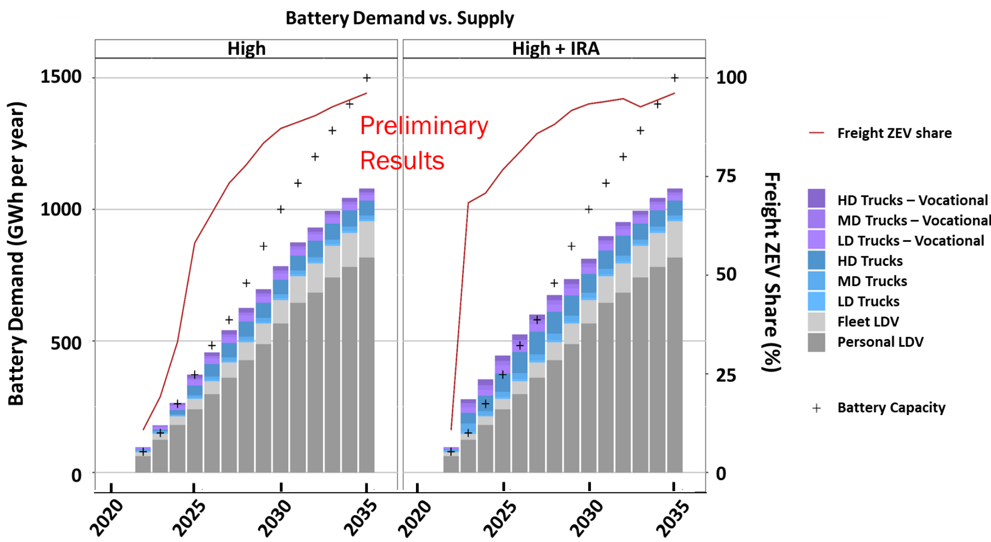


Figure IV.2.2 Battery supply and demand estimates and implications for EV adoption in IRA and non-IRA scenarios. Source: NREL

Finally, we also highlight the recent publication of "Exploring decarbonization pathways for USA passenger and freight mobility" in *Nature Communications* [10]. This paper evaluated a range of passenger and freight decarbonization strategies in the United States across future scenarios of travel behavior, technology advancement, and policy levers. This study found multiple pathways to deep decarbonization in the transportation sector and identified clean electric grids and EV adoption in on-road sectors as key components for successful decarbonization strategies. This paper's publication was enabled by continued support for the TEMPO model and ongoing model development and maintenance efforts. Additional efforts on developing light-, medium-, and heavy-duty EV charging behavior (the fourth TEMPO enhancement) have informed past publications (including [1] and [7]) and ongoing efforts conducted by NREL and EPRI and funded by DOE to model the impact of EVs on the bulk power system. Efforts to expand passenger travel modes (the fifth TEMPO enhancement) will support the DOE-funded work on micromobility and travel demand management.

Conclusions

Continued support for the TEMPO model in FY 2023 has enabled implementation of substantial model enhancements, allowing the analysis of additional scenarios that were previously outside of the model's scope. These include enhancements to the model's ability to analyze LDV adoption targets, implementation of key IRA provisions for passenger and freight vehicles, and consideration of supply chain constraints in demand projections. Additional ongoing model developments have enabled improved modeling of LDV charging profiles and extensions of the charging profile module to MHDVs, as well as improved representation of a broader range of passenger modes. These improvements allow TEMPO to evaluate a broader range of scenarios, encompassing the most up-to-date policy landscape; to understand key areas of uncertainty surrounding the impact of EVs on the electric grid; and to offer new insights into proposed policies, such as light-duty EV adoption targets. In addition, support provided by this project allowed the TEMPO team to hire and train additional staff, expanding the team's capacity to address additional research questions. An example of TEMPO's continued impact includes published analysis on the adoption of zero-emission MHDVs [12], which was extensively cited by the U.S. Environmental Protection Agency in its proposed rulemaking [13]. As this project progresses, we anticipate that the support provided for TEMPO will enable continued improvements in workflow, model maintenance and documentation, and model enhancements. These improvements will ensure that TEMPO continues to be a key tool to support VTO—and DOE in general—on a variety of critical topics, providing scenario analysis and timely quantitative insights to inform decision-making.

Key Publications

1. Hale, E., L. Lavin, A. Yip, B. Cowiestoll, J. Zhang, P. Jadun, and M. Muratori. 2022. Electric Vehicle Managed Charging: Forward-Looking Estimates of Bulk Power System Value. NREL. NREL/TP-6A40-83404. https://www.nrel.gov/docs/fy22osti/83404.pdf.

2. Hoehne, C., M. Muratori, P. Jadun, P., B. Bush, A. Yip, C. Ledna, L. Vimmerstedt, K. Podkaminer, and O. Ma. 2023. "Exploring decarbonization pathways for USA passenger and freight mobility." Nature Communications 14 (6913). https://www.nature.com/articles/s41467-023-42483-0.

3. Yip, Arthur, Christopher Hoehne, Paige Jadun, Catherine Ledna, Elaine Hale, and Matteo Muratori. 2023. Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States: Results From and Methods Behind Bottom-Up Simulations of County-Specific Household Electric Vehicle Charging Load (Hourly 8760) Profiles Projected Through 2050 for Differentiated Household and Vehicle Types. NREL. NREL/TP-5400-83916. https://www.nrel.gov/docs/fy23osti/83916.pdf.

References

1. Jadun, P., M. Muratori, C. Ledna, A. Yip, C. Hoehne, and B. Borlaug. 2023. "Holistic Modeling of Future Transportation Energy Use and Emissions: Transportation Energy and Mobility Pathway Options (TEMPO) Model." DOE VTO 2023 Annual Merit Review and Peer Evaluation Meeting, Washington, DC.

2. U.S. Drive. 2020. Vehicle-Mobility Systems Analysis Tech Team Roadmap. https://www.energy.gov/eere/vehicles/articles/vehicle-mobility-systems-analysis-tech-team-roadmap.

3. Muratori, M., P. Jadun, B. Bush, C. Hoehne, L. Vimmerstedt, A. Yip, J. Gonder, E. Winkler, C. Gearhart, and D. Arent. 2021. "Exploring the future energy-mobility nexus: The transportation energy & mobility pathway options (TEMPO) model." Transportation Research Part D: Transport and Environment 98: 102967. https://doi.org/10.1016/j.trd.2021.102967.

4. Decarbonizing Energy through Collaborative Analysis of Routes and Benefits, https://www.energy.gov/eere/decarbonizing-energy-through-collaborative-analysis-routes-and-benefits

5. Energy Modeling Forum, Stanford Engineering. n.d. "EMF 37: Deep Decarbonization & High Electrification Scenarios for North America." Accessed 2023. https://emf.stanford.edu/emf-37-deep-decarbonization-high-electrification-scenarios-north-america.

6. U.S. Department of Energy, U.S. Department of Transportation, U.S. Environmental Protection Agency, and U.S. Department of Housing and Urban Development. 2022. The U.S. National Blueprint for Transportation Decarbonization. Washington, DC. https://www.energy.gov/sites/default/files/2023-01/the-us-national-blueprint-for-transportation-decarbonization.pdf.

7. Yip, Arthur, Christopher Hoehne, Paige Jadun, Catherine Ledna, Elaine Hale, and Matteo Muratori. 2023. Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States: Results From and Methods Behind Bottom-Up Simulations of County-Specific Household Electric Vehicle Charging Load (Hourly 8760) Profiles Projected Through 2050 for Differentiated Household and Vehicle Types. NREL. NREL/TP-5400-83916. https://www.nrel.gov/docs/fy23osti/83916.pdf.

8. Hale, E., L. Lavin, A. Yip, B. Cowiestoll, J. Zhang, P. Jadun, and M. Muratori. 2022. Electric Vehicle Managed Charging: Forward-Looking Estimates of Bulk Power System Value. NREL. NREL/TP-6A40-83404. https://www.nrel.gov/docs/fy22osti/83404.pdf.

9. Binsted, M., H. Suchtya, Y. Zhang, L. Vimmerstedt, M. Mowers, C. Ledna, M. Muratori, and C. Harris. 2022. Renewable Energy and Efficiency Technologies in Scenarios of U.S. Decarbonization in Two Types of Models: Comparison of GCAM Modeling and Sector-Specific Modeling. NREL and Pacific Northwest National Laboratory, NREL/TP-6A20-84243; PNNL-33512. https://www.nrel.gov/docs/fy23osti/84243.pdf.

10. Hoehne, C., M. Muratori, P. Jadun, P., B. Bush, A. Yip, C. Ledna, L. Vimmerstedt, K. Podkaminer, and O. Ma. 2023. "Exploring decarbonization pathways for USA passenger and freight mobility." Nature Communications 14 (6913). https://www.nature.com/articles/s41467-023-42483-0.

11. U.S. Environmental Protection Agency. 2023. Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles – Draft Regulatory Impact Analysis. EPA-420-D-23-003. https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P10175J2.pdf.

12. Ledna, C., M. Muratori, A. Yip, P. Jadun, and C. Hoehne. 2022. "Decarbonizing Medium- & Heavy-Duty On-Road Vehicles: Zero-Emission Vehicles Cost Analysis." PowerPoint presentation. NREL. DOI: 10.2172/1854583.

13. U.S. Environmental Protection Agency. 2023. "Greenhouse Gas Emission Standards for Heavy-Duty Vehicles – Phase 3." 88 Fed. Reg. 25,926 (April 27, 2023) (to be codified at 40 CFR Parts 1036, 1037, 1054, 1065 and 1074). https://www.govinfo.gov/content/pkg/FR-2023-04-27/pdf/2023-07955.pdf.

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V Application and Accounting

V.1 Transportation Macroeconomic Accounting Models: VISION and Non-Light Duty Energy and Greenhouse Gas Emissions Accounting Tool (NEAT) (Argonne National Laboratory/National Renewable Energy Laboratory)

Yan Zhou, Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Lemont, IL 60439
E-mail: YZhou@anl.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: January 10, 2023 End Date: September 30, 2025
Project Funding (FY23): $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 greenhouse gas (GHG) emissions. To help research and develop technologies that can play a role in reducing those impacts, the Vehicle Technologies Office (VTO) needs strong analytical modeling capabilities to compare and evaluate the fleet impacts of vehicle and fuel technologies. Consistent, systematic approaches and methodologies should be employed to evaluate 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-, medium-, and heavy-duty vehicles; 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 (DOE) Office of Energy Efficiency and Renewable Energy (EERE) and other agencies to evaluate the impacts of advanced vehicle/fuel technologies. Programs employing these models include the VTO Analysis Program, Systems and Modeling for Accelerated Research in Transportation (SMART) Mobility, H2@Scale, and Transportation Decarbonization Analysis. 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 the Advanced Research Projects Agency–Energy, which uses the model 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 does the following:

- Annually updates and calibrates the VISION/NEAT models with projections from the U.S. Energy Information Administration's (EIA's) Annual Energy Outlook (AEO) reference case and the U.S. Department of Transportation's Freight Analysis Framework [3], [4].

- Enhances the medium- and heavy-duty (MDHD) modeling capabilities and increases the model's heterogeneity by adding flexible inputs for new mobility patterns and demographic variation that were developed in Fiscal Year (FY) 2021.
- Conducts scenario analysis to assess the regional carbon emissions of electric vehicle adoption in the United States, considering the variation in the grid mix, work that was developed in FY 2022.
- Examines the difference in emissions benefits estimated using generation-based and consumption-based emission intensities, work that was developed in FY 2023.

Objectives

The objective of this project has been to develop and update macroeconomic accounting model capabilities for the VTO Analysis Program and other programs, enabling users 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 benefit 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 and 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. Furthermore, by comparing the emissions benefits estimated using generation- and consumption-based emissions intensities, this project also shows the effects of cross-region electricity flows on regional GHG emissions.

Approach

VISION/NEAT covers over 10 on-road and off-road vehicle classes and over 20 different powertrain technologies. Figure V.1.1 shows the overall model framework, along with the vehicle technologies and transportation fuel pathways considered.

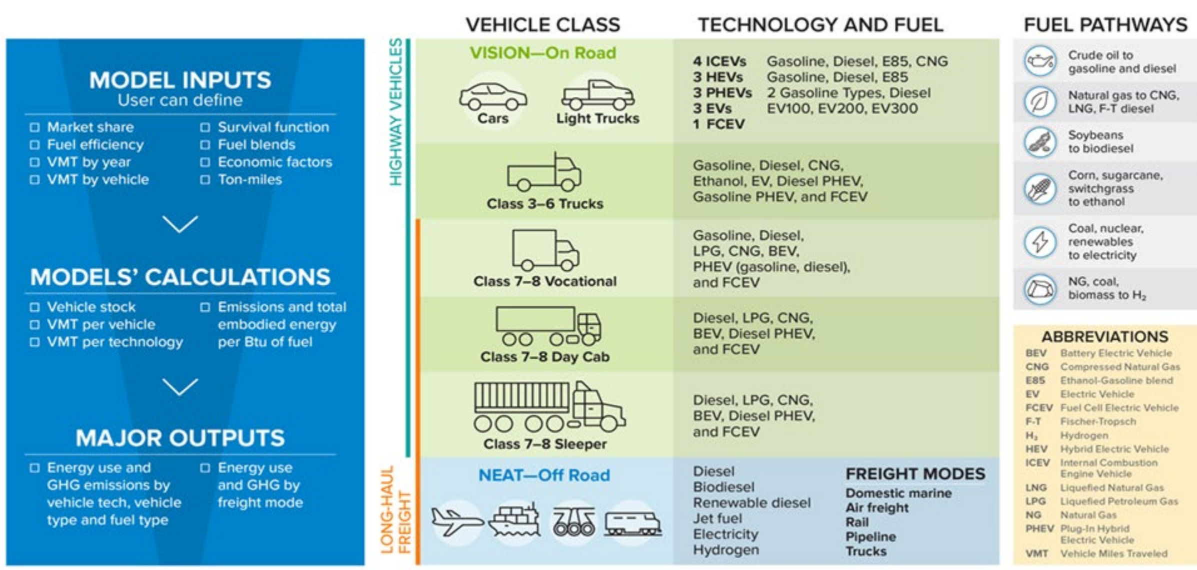

Figure V.1.1 VISION/NEAT model structure (VISION focuses on highway vehicle technologies; NEAT focuses on freight modes). Source: Argonne National Laboratory

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.1.2. 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.

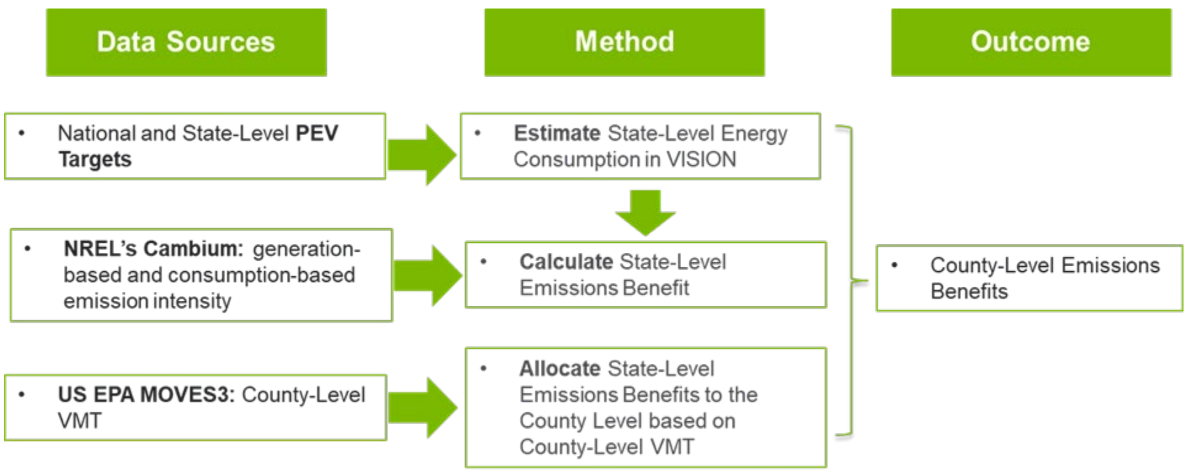

Figure V.1.2 Method for quantifying the distributed emissions impact of EV adoption and usage. Source: Argonne National Laboratory.

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 light-duty vehicles sold in the United States in 2030 will be PEVs [5]. Moreover, this study compares generation-based and consumption-based GHG emissions at the county level, across the nation, to show the necessity of taking consumption-based emissions into account.

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 Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) model [6]. GREET GHG coefficients account for the full fuel cycle. VISION 2022 has been updated to reflect (1) the EIA AEO 2022 Reference Case and (2) the 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 powertrain technologies: vocational single-unit trucks and day cab (regional) tractor–trailer combination trucks [7].

Figure V.1.3 shows the percentage of emissions reduction from accelerated (or targeted) PEV adoption compared with emissions under the AEO base case PEV market shares from 2020 to 2050. The plot shows data at the county level and is divided into two groups—states with PEV adoption targets vs. states without such targets—and three decades: the 2020s, 2030s, and 2040s. Regardless of the existence of PEV adoption targets, most states expect to see some level of emissions reduction in the next three decades. In general, as

PEV market shares increase, emissions reductions will also increase over the years. For states without PEV adoption targets, median percentages of emissions reduction at the county level increased from 3.5% to 24.7% from the 2020s to the 2040s, relative to the base case. For states with PEV adoption targets, median percentages of reduction at the county level are much higher, increasing from 4.9% to 41.2% during the same period. Moreover, as PEV market shares increase, the variation in emissions reduction becomes more substantial among states with PEV adoption targets because of differences in vehicle stocks and electricity grid mixes.

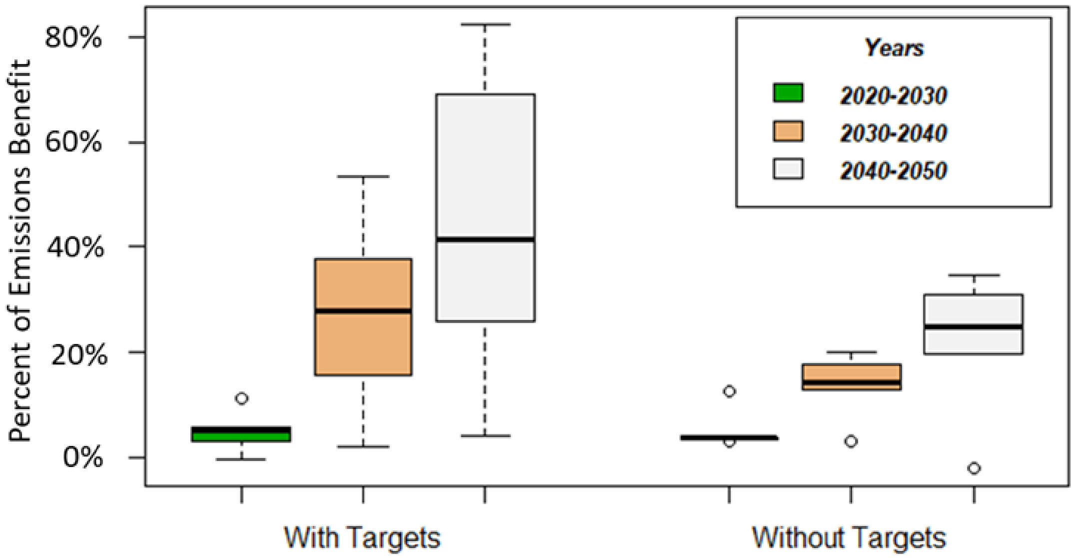

Figure V.1.3 Ranges of county-level emissions reduction from 2020 to 2050 between states with and without defined PEV adoption targets. The top and bottom of each bar represent the anticipated 75th and 25th percentile of county-level emission reductions, respectively. The line in the middle indicates the median. The top and bottom whiskers represent the maximum and minimum emission 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.1.4 [8]. 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 [9]. 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, high traffic volumes in the most populated metropolitan areas of each state (e.g., Chicago, Illinois, and the Twin Cities, Minnesota) lead to higher emissions benefits than are seen in other regions of the state.

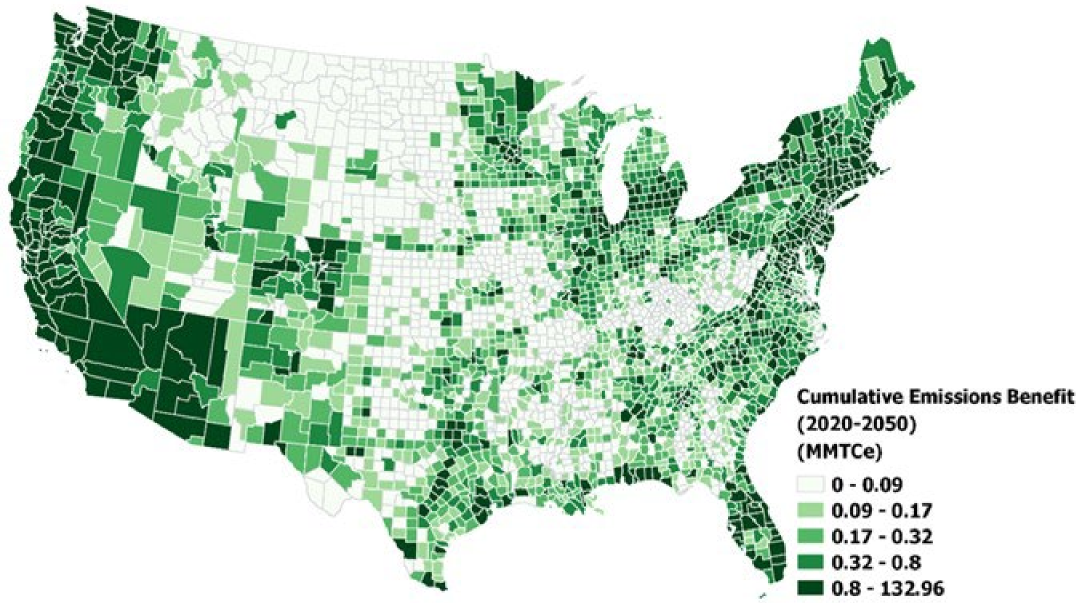

Figure V.1.4 Cumulative emissions benefits of PEV adoption in the lower 48 states compared to the base case PEV market share (2020–2050). Source: Argonne National Laboratory

In contrast, many regions show limited potential for emissions reduction. First, some of the least populated areas (e.g., most counties in North Dakota) do not see large emissions benefits, even as PEVs increasingly replace gasoline vehicles. Moreover, counties in regions with less clean electric grid mixes tend to have less potential for emissions reductions. For example, some parts of Indiana and Kentucky use high shares of coal in electricity generation, which leads to high carbon emissions intensities and less potential for emissions reductions.

Nationally, Los Angeles County, California, has the largest cumulative emissions reduction (132.9 million metric tons of carbon equivalent [MMTCe]), thanks to its relatively clean grid and large VMT volume. At the state level, California has the largest cumulative emissions reduction (536.4 MMTCe), and North Dakota has the smallest (0.7 MMTCe).

Figure V.1.5 shows the difference in emissions benefits estimated using generation-based and consumption-based emissions intensities, respectively. In general, across the nation, differences between generation-based and consumption-based emissions at the county level range from -5.77 to +4.52 MMTCe for states like California, Texas, Florida, and West Virginia. If only generation-based emissions intensities are considered, the emissions benefit would be overestimated in many regions (red-shaded), such as California. This indicates that, despite having a relatively clean grid, California tends to shift some of its upstream emissions to adjacent electricity-exporting regions. In contrast, emissions benefits could be underestimated (blue-shaded) in states like Missouri and Indiana, which still rely heavily on coal for electricity generation and export large amounts of coal-based electricity.

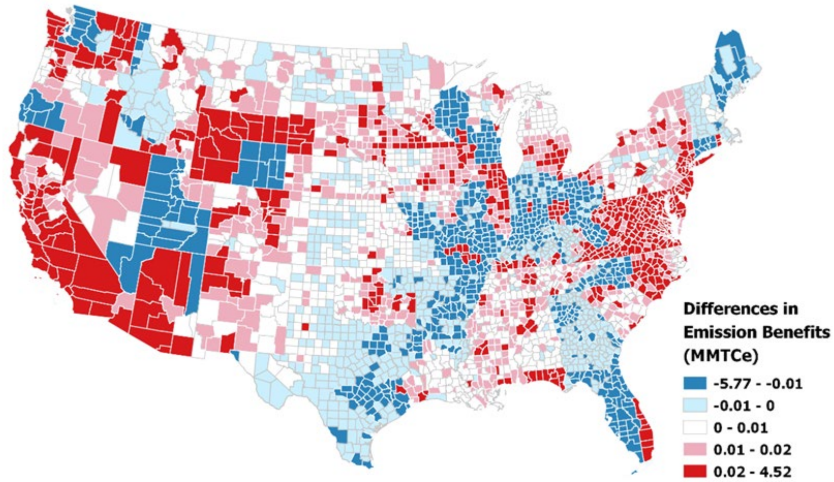

Figure V.1.5 Differences in emission benefits by county, estimated by using generation-based and consumption-based emission intensities. Source: Argonne National Laboratory

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. These models are used to evaluate the impacts of advanced vehicle technologies. VISION/NEAT has over 8,000 users.

In this project, VISION/NEAT was fully updated to match the projections in the EIA AEO 2022 Reference Case. VISION/NEAT was 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 PEV adoption will have nationwide emissions benefits. For states without defined PEV adoption targets, median percentages of emissions reduction at the county level could increase from 3.5% to 24.7% over the next three decades. In comparison, states with PEV adoption targets have higher median rates of emissions reduction at the county level, increasing from 4.9% to 41.2% over the next three decades. PEV adoption targets, electric grid mixes, and VMT all affect the magnitude of achievable emissions reduction and lead to geographic variations in emissions benefits. At the county level, cumulative emissions benefits range from 0 to 133 MMTCe.

Furthermore, by comparing the emissions benefits estimated using generation- and consumption-based emissions intensities, this project shows the effect of cross-region electricity flows on regional GHG emissions. Through the trade of power across regions, developed areas with cleaner grids could shift some of their upstream emissions to areas with relatively more polluting grids.

Key Publications

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

2. Wu, X., Y. Zhou, D. Gohlke, and J. Kelly. 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, DC.

References

1. Argonne National Laboratory. n.d. VISION model. Accessed 2023. https://www.anl.gov/es/vision-model.

2. Argonne National Laboratory. n.d. NEAT model. Accessed 2023. https://www.anl.gov/es/neat-nonlight-duty-energy-and-ghg-emissions-accounting-tool.

3. EIA. 2020. "Annual Energy Outlook 2020." https://www.eia.gov/outlooks/aeo/.

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

5. The White House. 2021. "FACT SHEET: President Biden Announces Steps to Drive American Leadership Forward on Clean Cars and Trucks." August 5. 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/.

6. Argonne National Laboratory. n.d. GREET: The Greenhouse gases, Regulated Emissions, and Energy use in Technologies Model. Updated October 2022. https://greet.anl.gov/.

7. Experian Automotive. n.d. Vehicle in Operation Market Data & Reports. Data Set. Accessed November 8, 2021. https://www.experian.com/automotive/vehicles-in-operation-vio-data.

8. National Renewable Energy Laboratory. 2021. Cambium Documentation: Version 2021. https://www.nrel.gov/docs/fy22osti/81611.pdf.

9. Multi-State ZEV Task Force. 2018. *Multi-State ZEV Action Plan: 2018–2021*. https://www.nescaum.org/documents/2018-zev-action-plan.pdf.

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VI Integrated Analysis

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

Michael Wang, Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Argonne, IL 60439
E-mail: MQWang@anl.gov

Amgad Elgowainy, Co-Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Argonne, IL 60439
E-mail: AElgowainy@anl.gov

Jarod Kelly, Co-Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Argonne, IL 60439
E-mail: JCKelly@anl.gov

Zifeng Lu, Co-Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Lemont, IL 60439
E-mail: ZLu@anl.gov

Chris Kolodziej, Co-Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Lemont, IL 60439
E-mail: CKolodziej@anl.gov

Patrick Walsh, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Patrick.Walsh@ee.doe.gov

Start Date: October 1, 2022 End Date: September 30, 2025
Project Funding (FY23): $500,000 DOE share: $500,000 Non-DOE share: $0

Project Introduction

Supported by the U.S. Department of Energy (DOE) since 1994, the Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET®) model is an instrumental tool for life cycle analysis (LCA). Both frameworks of the tool (Excel and .Net versions) are updated and released to the public annually. The updates reflect state-of-the-art fuel and vehicle technologies and emerging LCA issues. This project supports deep technical analysis that benefits the model. The project also uses GREET® to support research tasks such as those of the U.S. DRIVE Integrated Systems Analysis Tech Team (ISATT) program and important quick-turn-around analysis requests from DOE.

Expansion and Update of GREET 2 Modeling and Capabilities

Task Introduction

This task updates and evaluates vehicle parameters including operational characteristics, vehicle component masses, and vehicle component material compositions. The work also includes critical LCA issues related to materials, including the treatment of material recycling and consistent and continuous materials supply chain analysis. These activities are necessary:

- To identify the hot spots along materials supply chains for energy use, greenhouse gas (GHG) emissions, and other environmental burdens. Supply chain analysis incorporates supply-chain-related factors in calculating environmental burdens (e.g., ore type and technologies used for material production, localized energy input parameters).

- To evaluate the up-to-date energy and environmental burdens of producing the associated automotive materials and components and, thus, the final vehicle. A LCA is used to make these determinations.

For this analysis, Argonne National Laboratory (ANL) configured and updated the GREET® model with the most recent available data. The GREET® model includes different vehicle classes (sedan, pickup truck, sport utility vehicle [SUV], and a variety of heavy-duty truck classes) with different powertrains (internal combustion engine vehicles [ICEVs], hybrid electric vehicles [HEVs], plug-in hybrid electric vehicles [PHEVs], battery electric vehicles [BEVs], and fuel-cell electric vehicles [FCEVs]). This task focuses on GREET® model development and expansion for new vehicle technologies, vehicle classes, and fuel production pathways and for emerging LCA issues that require reliable LCA results of vehicle/fuel systems.

Objectives

The objectives of this task are to:

- Advance GREET® modeling by expanding the treatment of energy and emission credits at the end of life (EOL) for vehicle components in GREET 2 to inform the vehicle manufacturing cycle analysis.

- Extend the modeling of critical automotive materials to be consistent with the state of the art, with a focus this year on aluminum (Al) disaggregation.

- Update all vehicle energy consumption and mass characteristics within the GREET® model to represent the latest available data.

Approach

In Fiscal Year (FY) 2023, ANL undertook several important subtasks. First, we expanded the modeling of energy and emission credits of end-of-life recycling (EOLR) of vehicle components in GREET 2 to inform the vehicle manufacturing cycle analysis and evaluate the impacts of material displacement from a global supply chain perspective. Historically, GREET 2 used the recycled content (RC) approach, as commonly practiced in the LCA community, to address the recycling of key vehicle materials. Using the new EOLR credit approach, implemented recently, the energy and emission credits of recycled materials in used vehicles are estimated and credited specifically to the original vehicles. The EOLR credit approach addresses the recycling of vehicle materials and their new uses, thus enabling detailed circular economy analysis of vehicles and vehicle EOL. Furthermore, the EOLR approach allows evaluations of material recycling's potential impacts on global supply chains. These details for selected materials are integrated into the GREET 2 portion of the model.

Next, ANL continued to improve material modeling for GREET® by expanding its LCA of Al, specifically by revising the characterization of wrought Al into a disaggregated set of Al sheet and extruded Al. This effort builds upon prior studies and ANL's own efforts [1], [2]. The integration effort was incorporated into GREET 2.

Finally, ANL continued to revise vehicle performance parameters within GREET® based on results from ANL's Autonomie modeling [3]. Doing this ensures that ANL remains consistent with the latest developments in vehicle technologies. All of the energy consumption parameters for the light-duty vehicles (LDVs: cars, SUVs, and pickup trucks) and medium- and heavy-duty vehicles (MHDVs) are integrated into the GREET 1 model. The vehicle mass characteristics are incorporated into GREET 2 for the cars, SUVs, and pickup trucks and for a subset of the MHDVs, namely Class 6 box trucks and Class 8 long-haul and regional-haul trucks.

Results

We expanded the capabilities of the EOLR approach to incorporate additional materials and to update the share of RC for these materials in vehicles. These materials include those for which material and energy flow data (i.e., life cycle inventory [LCI] data) is available for their recycled versions in GREET®, as well as those for which such LCI was not available. Updates have been made in the GREET 2023 model, subject to data availability in the literature. Table VI.1.1 details the parameters for RC and EOLR approaches updated in GREET 2023. While we incorporated details for lead, nickel, and magnesium into this year's updates, we also investigated automotive glass, plastics, and platinum for both their RC and EOL recycling rates but had inconclusive results from the data available.

Table VI.1.1 Shares of Different Material Origins in Semi-Fabricated Al Products

Material	RC Share (%) in LDVs		EOL (GREET 2023)		
	GREET 2022	GREET 2023	Collection rate (%)	Processing rate (%)	Recycling rate (%)
Lead	73	100			99
Nickel	44	44			80
Magnesium	52.1	52.1			70
Copper	Not Applicable	Inconclusive	91	54	49

Lead is used in lead–acid start-up batteries of various LDVs. Prior GREET® versions noted a 73% RC for lead used in these batteries, with the remaining coming from primary lead metal [4], [5], [6]. However, the project team conducted a literature review that suggested a significant increase, with indications that each part of the lead–acid battery is recycled back into a new battery, indicating a 100% RC share [7]. Another study states that a typical lead–acid battery comprises 85% recycled material, with sulfuric acid and fiberglass being the primary virgin components [8]. A study by Battery Council International reports, from an EOLR perspective, an overall ~99% lead recycling rate—inclusive of lead collection and processing rates for recycling [9]. Hence, ANL used the value of 100% for RC share and 99% for EOLR rate in the updated GREET 2023 model as indicated in Table VI.1.1 above.

For nickel, GREET® previously assumed a 44% RC rate for LDVs. No new data were available to recommend a change to this RC value. Given the lack of more recent data, we retained the same RC share of nickel in GREET 2023. However, for the EOLR approach, we assume an 80% recycling rate, based on the literature [10].

As with nickel, no new data from the literature could be found to update RC share for magnesium. However, a significant amount of magnesium in vehicles is recovered along with Al and mixed with it to produce Al alloys, while a small share is recovered as the metal itself [11], [12]. Hence, we keep the same RC content for magnesium as in previous GREET® versions while considering a 70% recycling rate for the EOLR approach, per [12]. This includes magnesium recycled both in the form of an alloy (with Al) and as an unalloyed metal.

Previous GREET® versions have not considered any copper recycling, and the literature review did not yield any RC data for this element. However, for the EOLR approach, a study on global copper flows and stocks

[13] indicates that its post-use collection rate is 91% and that its processing rate is at 54%, translating into a recycling rate of 49%.

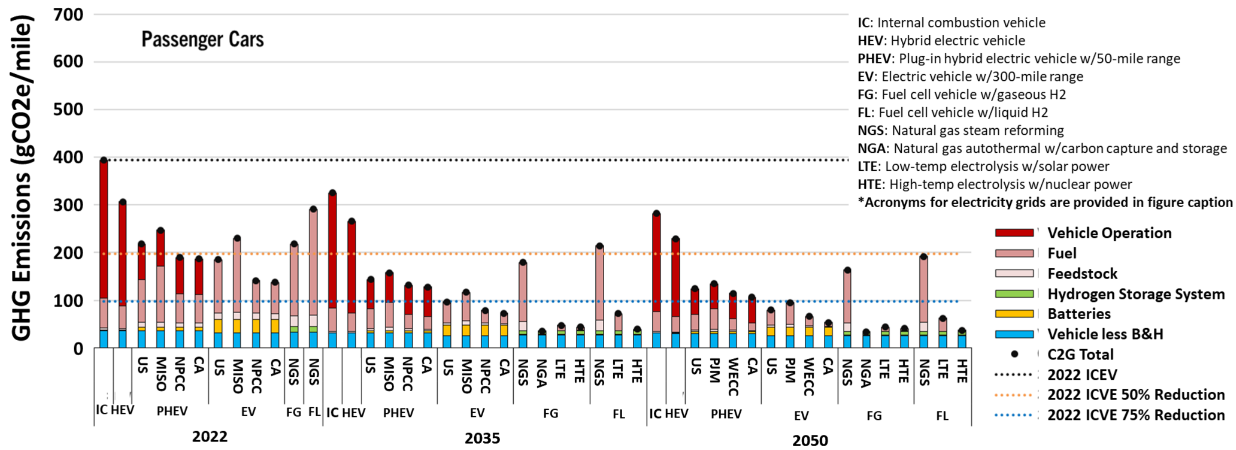
Al is used extensively in various semi-fabricated forms across transportation, residential, commercial, and industrial end-use sectors. Since these forms are processed via divergent routes that result in differences in their respective life cycle GHG intensities, we account for the appropriate Al form corresponding to the application concerned. Furthermore, Al can be highly GHG- and cost-intensive when processed using virgin ore, so a considerable share of its production comes from either recycled or scrap Al sources. The Al shares from these different sources (virgin, recycled, and scrap) must be considered for each Al form while accounting for the sources' respective GHG intensities.

In FY 2023, ANL built upon its earlier work on expanding the Al forms in GREET® (for automotive and non-automotive applications) [2] and modified the shares of Al sources in their respective production as indicated in Table VI.1.1 to make them representative of current-day data. This also influences the life cycle GHG intensity of these forms as shown in Table VI.1.1 and based on the North American Al consumption mix. We also removed the additional classifier of wrought Al (used in previous GREET® versions). Instead, we reverted to the direct use of its components (automotive extruded Al and cold-rolled/stamped Al sheets) to compute vehicular Al GHGs. Implementing this change across each vehicle and its components within GREET® was an extensive task that required coordination of hundreds of vehicle components across the two GREET® platforms. With this expansion, GREET® becomes a more flexible and user-friendly environment for users. This change was requested by several industry partners with whom ANL communicates regularly through the ISATT program (see Task 3 under this project) and on other projects.

Table VI.1.1 Shares of Different Sources in Semi-Fabricated Al Products and Their Respective Life Cycle GHG Intensities

Form of Al/Al Feedstock	Non-Automotive			Automotive	
	Extruded Al	Al sheet	Al foil	Extruded Al	Stamped Al
Virgin	39%	20%	20%	27%	50%
Recycled	30%	23%	23%	16%	0%
Scrap	31%	57%	57%	57%	50%
GHG Intensity (kilograms CO_2-eq/kilogram)	6.5	4.1	4.7	4.8	11.9

Finally, GREET® relies upon vehicle specifications associated with energy consumption and vehicle mass, as developed by ANL's Autonomie modeling team [3], to remain current with technology advancements. These updates are integrated into multiple platforms in GREET® to adjust the fuel economy of all existing vehicle technologies. This directly informs the associated well-to-wheels (WTW) energy and emissions of these vehicles. Furthermore, the vehicle mass characteristics for these vehicles are incorporated into GREET 2 (and .Net) for the cars, SUVs, pickup trucks, and Class 6 box trucks, and Class 8 long-haul and regional-haul trucks. This type of analysis allows ANL to develop complete cradle-to-grave (C2G) analyses for a variety of vehicle technologies. An example of such a C2G result is presented in Figure VI.1.1. This chart shows how the life cycle GHG impacts of passenger cars change over time and are subject to a variety of fueling pathways. It presents ICEVs, HEVs, PHEVs, EVs, and FCEVs fueled by differing conventional and advanced fuels. Note that fuel cell vehicles can utilize hydrogen that has been transported in either a gaseous or liquid form. The figure indicates that deep carbonization pathways exist for the investigated vehicle technologies if they are indeed operated on advanced fueling pathways.



US: US average; MISO: Midcontinent Independent System Operator; NPCC: Northeast Power Coordinating Council; CA: State of California average; FRCC: Florida Reliability Coordinating Council; PJM: Pennsylvania–New Jersey–Maryland Interconnection; WECC: Western Electricity Coordinating Council

Figure VI.1.1 C2G GHG emissions for passenger cars. Results for PHEVs and EVs are presented with U.S. average electricity grid, grids with the highest and lowest carbon intensity for each simulation year, and the state of California average grid. Source: ANL

Conclusions

This task updated and expanded the GREET® model's LCA methodological capabilities by incorporating additional materials that can be included in comparisons of the RC and EOLR life cycle burdens of materials. These improvements allow for deeper insights into not only the current state of the market, which is typically indicated by the RC method, but also what the market could look like in the future, which is typically indicated by the EOLR method. This task also updates selected material LCIs; in FY 2023, the project focus was for Al. By expanding Al from an aggregate wrought product to both sheet and extrusion, we have allowed users much greater flexibility in their modeling and provided better representation of the market. Finally, we updated vehicle specifications within GREET® to ensure that the model continues to allow for the most up-to-date LCA studies for both WTW and C2G analyses.

Key Publications

1. Iyer, R. K., J. C. Kelly, and A. Elgowainy. 2023. "Vehicle-Cycle and Life-Cycle Analysis of Medium-Duty and Heavy-Duty Trucks." Science of the Total Environment. May 19. DOI: 10.1016/j.scitotenv.2023.164093.

2. Iyer, R. K., Q. Dai, and J. C. Kelly. 2023. Nickel Life Cycle Analysis: Updates and Additions in the GREET Model (Rev. 1). Argonne National Laboratory.

3. Iyer, R. K., and J. C. Kelly. 2023. Updates to Medium-Duty & Heavy-Duty Vehicle Component Weights. Argonne National Laboratory.

4. Iyer, R. K., S. Shukla, and J. C. Kelly. 2023. Nickel Updates in GREET 2023. Argonne National Laboratory.

5. Kelly, J. C., R. K. Iyer, and C. Kolodziej. 2023. End-of-Life Recycling Information for Lead, Nickel, Magnesium, Copper, Glass, Plastic, and Platinum. Argonne National Laboratory. September.

Vehicle Technologies Office. 2023. "Fact of the Week #1303: From Cradle to Grave, Electric Vehicles Have Fewer Greenhouse Gas Emissions Than Conventional Vehicles." August 14. https://www.energy.gov/eere/vehicles/articles/fotw-1303-august-14-2023-cradle-grave-electric-

vehicles-have-fewer#:~:text=The%20analysis%20showed%20that%20EVs,be%20available%20in%202030%E2%80%922050.

Select Presentations

1. Kelly, J., and R. Iyer. 2023. “Vehicle-Cycle and Life-Cycle Analysis of Medium-Duty & Heavy-Duty Trucks in the United States.” CRC Sustainable Mobility Committee – Partner Member Group and Steering Committee Meeting. August 3.

2. Kelly, J. 2023. “Automotive Life Cycle Analysis: Trends and Perspectives.” Konkuk University, Seoul, Korea. September 14.

References

1. Wang, M. 2022. *The Environmental Footprint of Semi-Fabricated Al Products in North America: A Life Cycle Assessment Report*. TheAl Association. January. https://www.aluminum.org/sites/default/files/2022-01/2022_Semi-Fab_LCA_Report.pdf.

2. Iyer, R, and J. Kelly. 2022. *Updates on Inventory of Al Production*. Argonne National Laboratory. October.

3. Islam, Ehsan Sabri, Daniela Nieto Prada, Ram Vijayagopal, and Aymeric Rousseau. 2023. “Detailed Simulation Study to Evaluate Future Transportation Decarbonization Potential.” Report to the U.S. Department of Energy, Contract ANL/TAPS-23/3. October.

4. Burnham, A., M. Wang, and W. Yu. 2006. “Development and Applications of GREET 2.7 – The Transportation Vehicle-Cycle Model.” ANL/ESD/06-5. DOI: 10.2172/898530. https://publications.anl.gov/anlpubs/2006/12/58024.pdf.

5. Burnham, A. 2012. “Updated Vehicle Specifications in the GREET Vehicle-Cycle Model.” Argonne National Laboratory. July.

6. Wang, M., A. Elgowainy, U. Lee, et al. 2022. “Summary of Expansions and Updates in GREET® 2022.” Argonne National Laboratory.

7. CJD E-Cycling. 2017. “Lead-Acid Battery Recycling: What You Need to Know.” https://www.cjdecycling.com/lead-acid-battery-recycling-need-know/.

8. Karden, E. 2017. “Development trends for future automobiles and their demand on the battery.” *Lead-Acid Batteries for Future Automobiles*: 3–25. https://doi.org/10.1016/B978-0-444-63700-0.00001-5.

9. SmithBucklin Statistics Group. 2019. *National Recycling Rate Study*. November. https://batterycouncil.org/wp-content/uploads/2019/11/BCI_433784-19_RecyclingRateStudy_19Update_FINAL.pdf.

10. Ortego, A., A. Valero, A. Valero, and M. Iglesias. 2018. “Downcycling in automobile recycling process: A thermodynamic assessment.” *Resources, Conservation and Recycling* 136 (September): 24–32. https://doi.org/10.1016/j.resconrec.2018.04.006.

11. Ehrenberger, S., and H. E. Friedrich. 2013. “Life-cycle assessment of the recycling of magnesium vehicle components.” JOM: the journal of the Minerals, Metals & Materials Society 65(10): 1303–1309. DOI: 10.1007/s11837-013-0703-3.

12. Golroudbary, S. R., I. Makarava, E. Repo, and A. Kraslawski. 2022. "Magnesium Life Cycle in Automotive Industry." *Procedia CIRP* 105 (2): 589–594. DOI: 10.1016/j.procir.2022.02.098.

13. Glöser, S., M. Soulier, and L. A. Tercero Espinoza. 2013. "Dynamic analysis of global copper flows. Global stocks, postconsumer material flows, recycling indicators, and uncertainty evaluation." *Environmental Science and Technology* 47(12): 6564–6572. DOI: 10.1021/es400069b.

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Offroad decarbonization opportunities with expanded GREET®

Task Introduction

Offroad vehicles consist of vehicles used within the construction, agriculture, and recreation sectors, as well as many other sectors. These types of vehicles can be distinguished by size, weight, usage, and/or power demand. Such vehicles include farming tractors, excavators, bulldozers, airport service equipment, and a host of other equipment. As noted, there may be a wide range of vehicles within each application.

These offroad vehicles typically use diesel fuel or gasoline, and they are often subject to tailpipe exhaust emissions standards but not efficiency regulations. Government and industrial efforts have begun to reduce GHG emissions of these vehicle types, with potential decarbonization pathways mirroring those afforded within the on-road sector. One method is efficiency improvement through engine advancement or hybridization. Others include using low-carbon fuels, using fuel cell technologies, and adapting these vehicles for fully electric powertrains. Each approach has its own technical merits and challenges. There is a need to understand the degree to which the different powertrain technology options and fuel options reduce life cycle GHG emissions. The GREET 1 model has many fuel pathways for on-road vehicles. In addition, the model contains emissions factors for several offroad vehicle types that use conventional fuels. However, it does not have the same completeness and coverage for alternative fueling pathways and advanced powertrain systems for offroad vehicles.

The GREET 2 model also contains vehicle cycle modeling of selected light-, medium-, and heavy-duty on-road vehicles, which allows for the determination of a vehicle's total life cycle performance. The development of vehicle cycle modeling for offroad vehicles facilitates a deeper understanding of how the LCA is affected by various factors associated with the vehicles' manufacture. For instance, vehicle electrification improves vehicle efficiency, but it requires large battery packs to provide adequate energy for operation. The battery itself for a 300-mile-range LDV can represent a 50% increase in vehicle cycle GHG emissions compared to an ICEV.

Objectives

By adding vehicle cycle simulation for offroad vehicle types, we address what vehicle manufacturing might look like for an offroad vehicle, such as an excavator or a bulldozer, if it was electrified, given the duty cycle and lifetime of its operation.

The expanded GREET® model includes not only the energy consumption and emissions associated with the conventional powertrains in the offroad sector but also those associated with low-carbon fuels and advanced powertrains. The project team uses comprehensive LCA of offroad vehicles—conducted in coordination with the Vehicle Technologies Office (VTO) Decarbonization of off-road, Rail, Marine and Aviation program—to enable the GREET® model to help identify the opportunities and challenges of decarbonizing offroad vehicles.

Approach

The project team analyzed the U.S. Environmental Protection Agency (EPA) MOtor Vehicle Emission Simulator (MOVES) offroad equipment carbon dioxide (CO_2) inventory. Findings indicate that agricultural tractors produce 17% of CO_2 emissions from the full offroad sector, and they produce the highest CO_2

emissions of any particular type of offroad vehicle [1]. High-horsepower tractors (>175 hp) were responsible for approximately 75% of all tractor CO_2 emissions. Therefore, the first offroad vehicle added to GREET 2023 was a large 300 hp four-wheel-drive agricultural tractor. As with heavy-duty on-road vehicles, ANL added new sheets to GREET 1 for agricultural tractor fuel cycle (e.g., WTW) analysis, GREET 2 for vehicle cycle analysis, and C2G analysis when combining fuel cycle and vehicle cycle results.

Four tractor powertrain options were added: ICEV, HEV, EV, and FCEV. Within GREET 1, users can select from conventional sources of fuel and electricity or from a variety of low-carbon fuel and electricity pathways. Results include life cycle WTW energy and water consumption, GHG emissions, and emissions of criteria air pollutants. Since fuel cycle GHG emissions vary with the energy consumption rate, GREET® users are able to designate what percentage of tractor operating hours are spent at low, medium, and high loads. Autonomie vehicle simulations were used to generate default energy consumption rates of a large tractor performing a chisel plow operation for each powertrain option and load [2].

In GREET 2, the vehicle-cycle energy consumption, water consumption, GHG emissions, and criteria air pollutant emissions are calculated. The GREET® user can adjust the tractor's operating profile (number of hours per year and hours per vehicle lifetime), bill of materials (including powertrain components, chassis, etc.), fluid capacities, and life cycle component and fluid replacements. The default agricultural tractor had 550 hours of operation per year (per the EPA) [1]; thus, the total lifetime operation of 15,000 hours was selected based on previous agricultural tractor life cycle survey data [3]. Total tractor weight, as well as subsystem weights (engine or fuel cell, chassis, electric motors, hydrogen tank, and batteries) were determined through iterations with the Autonomie vehicle modeling effort. Conventional large diesel-powered tractors operating in four-wheel drive can operate for approximately 20 hours continuously at 75% of pull [4]. In this work, the battery (for the battery electric tractor) and hydrogen tank (for the fuel cell tractor) were sized to allow for 10 hours of continuous operation at 75% of pull based on information from the University of Kentucky [5]. Assuming a 90% depth of discharge, the full electric tractor would require a 1.88 MWh battery capacity, which would weigh approximately 25,000 lbs. and more than double the tractor weight compared to the conventional diesel tractor. Notably, even with such a heavy battery weight addition, the total tractor weight would still be less than the maximum ballasted tractor weight [6]. However, there would be challenges in distributing the additional battery system weight to be well-supported by the tractor chassis and to ensure no negative effects on the tractor's pulling performance or soil compaction (and crop yield). Tire sizes and mass were set based on an equivalent large John Deere 8R 280 tractors [4]. Fluid capacities and replacement schedules were based on John Deere information for John Deere 8 series tractors [7]. Between the various tractor powertrain options, it was assumed that the non-powertrain systems (hydraulics, chassis, wheels/tires, cab, etc.) were the same.

Results

One of the key inputs to the fuel cycle analysis is the energy consumption rate of the tractor with each powertrain. Figure VI.1.2 shows the energy consumption rates of the conventional internal combustion engine (ICE), parallel hybrid electric, full battery electric, and fuel cell powertrains in terms of diesel gallon equivalent (DGE) per hour. All powertrains consumed more energy as load increased, with the energy consumption rate increasing the most with load for the fuel cell powertrain and the least for the full battery electric powertrain. The parallel hybrid powertrain lacked electric regeneration opportunities and experienced continuous operation and therefore, contrary to LDVs, did not offer energy consumption reductions. However, full battery electrification offered approximately 50% reductions in energy consumption rates, while the fuel cell powertrain allowed for 15%–20% lower energy consumption.

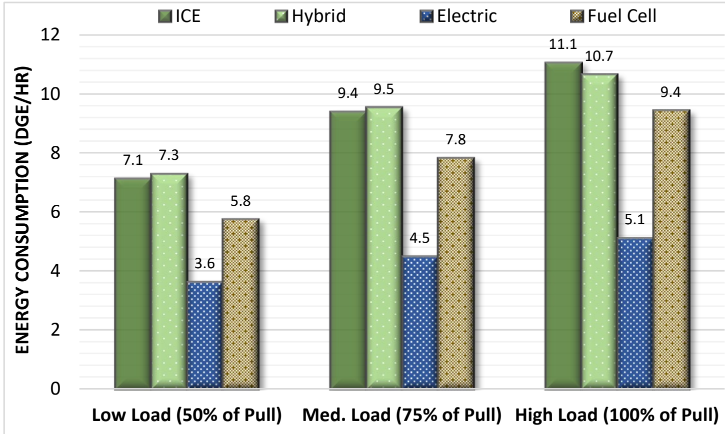
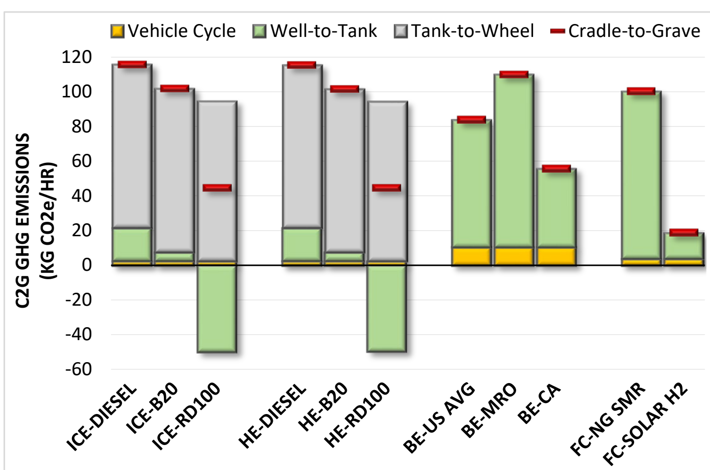


Figure VI.1.2 Energy consumption rates of a large agricultural tractor at low, medium, and high load with multiple powertrain options: internal combustion engine (ICE), parallel hybrid-electric (Hybrid), full battery electric (Electric), and fuel cell electric (Fuel Cell) in diesel gallon equivalent per hour (DGE/HR). Source: ANL

Using the energy consumption rates of each powertrain, the project team calculated fuel cycle GHG emissions. The fuel cycle consists of the well-to-tank (WTT) GHG emissions, which come from production and transportation/distribution of the fuel (or electricity); while the tank-to-wheel (TTW) GHG emissions result from the use of that energy during vehicle operation. Figure VI.1.33 shows the WTT (green) and TTW (gray) results of each powertrain with various current and reduced carbon energy sources.

For the ICE and hybrid electric powertrains, the majority of the WTW GHG emissions occurred during the TTW portion because of CO_2 emissions from engine combustion, while WTT GHG emissions were much lower. When the ICE and hybrid electric powertrains were fueled by a 20% biodiesel blend (B20) or 100% renewable diesel (RD100), the WTT GHG emissions were reduced toward zero (B20) or became significantly negative (RD100) (as a result of CO_2 uptake during biomass growth), driving down the WTW emissions. Since the battery electric and fuel cell tractors did not have any direct GHG emissions, their TTW GHG emissions were null, and the entirety of their WTW emissions were derived from their WTT energy production and transportation/distribution. Depending on the source of electricity (battery) or hydrogen (fuel cell), the WTW GHG emissions of those tractors could be significantly lower than the ICE and hybrid electric powertrains, or nearly as high as the conventional diesel-fueled ICE tractor.



HE – hybrid electric; BE – battery electric; FC – fuel cell; CA – California

Figure VI.1.3 C2G GHG emissions of a large agricultural tractor with multiple powertrain and fueling pathways. Source: ANL

Three current electrical grid carbon intensities are represented in Figure VI.1.3 for the battery electric tractor: U.S. average, Midwest Reliability Organization (MRO) region, and the California electrical grid. The MRO grid region was selected because it is where the highest population density of large agricultural tractors exists in the United States [8]. The MRO region also happens to be one of the highest-carbon-intensity electrical grids in the United States [9]. While California does not have as high of a large tractor population as the Midwest and Texas, it does have the lowest-carbon-intensity electrical grid in the United States and demonstrates the potential for WTW GHG reduction of battery electric tractors as the MRO grid carbon intensity decreases.

For the fuel cell tractor, the current practice of natural gas (NG) steam methane reforming (SMR) to produce hydrogen is shown to drive the WTW GHG emissions quite high. However, hydrogen production from green electricity (such as from solar energy) can reduce the fuel cell tractor WTW GHG emissions by more than 80%. To note, if low-carbon solar electricity were available to the battery electric tractor, it would also have similarly low WTW GHG emissions. This demonstrates the importance of low-carbon electricity and hydrogen availability, especially in the regions where large agricultural tractors are operated. The same could even be said for the WTT GHG emissions of low-carbon fuel (biofuel or e-fuel) production as the electrical grid drives toward zero carbon intensity.

As also seen in Figure VI.1.3, the third important piece of the life cycle GHG emissions is the vehicle cycle (yellow), which consists of the tractor manufacturing, operation/maintenance, and EOL (disposal/recycling) GHG emissions. As decarbonized electricity and fuel production drive toward net-zero (or even net-negative) WTW GHG emissions, the vehicle cycle will become increasingly more important in the total C2G life cycle GHG emissions. Because of the large battery capacity requirement (1.88 MWh for 10 hours of chisel plow operation) of the battery electric tractor, its vehicle cycle GHG emissions were twofold to fourfold higher than the vehicle cycle GHG emissions of the ICE tractor, with most of the GHG emissions coming from the battery. As battery production is also decarbonized, there are opportunities for the battery electric tractor vehicle cycle GHG emissions to decrease. Consequently, the technology's progress will need to be monitored and updated regularly.

Conclusions

The total C2G results of each tractor powertrain and energy pathway demonstrate that all have opportunities for deep decarbonization of large, high-power agricultural tractors: ICE tractors through net-zero carbon fuels (such as biofuels or e-fuels), battery electric tractors from low-carbon electricity production and battery manufacturing, and fuel cell tractors from low-carbon hydrogen production.

References

1. EPA. 2022. "Motor Vehicle Emission Simulator: MOVES3." Office of Transportation and Air Quality. Ann Arbor, MI.

2. Lajunen, A., K. Kivekas, V. Freyermuth, R. Vijayagopal, and N. Kim. 2023. "Simulation of Alternative Powertrains in Agricultural Tractors." In *36th International Electric Vehicle Symposium and Exhibition* (EVS36), Sacramento, California, June 11–14. https://evs36.com/wp-content/uploads/finalpapers/FinalPaper_Lajunen_Antti.pdf.

3. Mantoam, E. J., T. L. Romanelli, and L. M. Gimenez. 2016. "Energy demand and greenhouse gases emissions in the life cycle of tractors." Biosystems Engineering 151 (November): 158–170. https://doi.org/10.1016/j.biosystemseng.2016.08.028.

4. NTTL. 2021. "Nebraska OECD tractor test 2232 for John Deere 8R 280 e23 Diesel." Nebraska Tractor Test Laboratory, Lincoln, Nebraska. Retrieved from http://tractortestlab.unl.edu.

5. Hancock, J. N., Larry D. Swetnam, and F. J. Benson. 1991. "Calculating Farm Machinery Field Capacities." *Agricultural Engineering Extension Publications*. 20.

6. John Deere. 2023. "8 Series Tractors: 230-410 Engine Horsepower." Product brochure.

7. John Deere. 2022. “Replacement Parts Guide: 8R Tractor(s) Final Tier 4(FT4) (170001-) – 8R 230, 8R 250, 8R 280, 8R 310, 8R 340, 8R 370, 8R 410.” John Deere RX550516. November.

8. U.S. Department of Agriculture, National Agricultural Statistics Service. 2017. “Census of Agriculture: 2017 Publications.” https://www.nass.usda.gov/Publications/AgCensus/2017/index.php.

9. U.S. Energy Information Administration. 2023. “Annual Energy Outlook 2023.” March 16. https://www.eia.gov/outlooks/aeo/.

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

Task Introduction

In years past, ANL supported the U.S. DRIVE’s ISATT and published C2G studies for LDVs, including reports in 2016 and 2022. During FY 2023, ANL extended its efforts from the LDV space to conduct C2G analysis of MHDVs. ANL provided support to conduct a C2G GHG emissions LCA of MHDVs for selected vehicle classes of interest to the ISATT and the 21st Century Truck Partnership. The C2G of MHDVs leveraged the recent development in GREET® for Class 6 box trucks and Class 8 long-haul trucks across ICEV, HEV, FCEV, and BEV powertrains. For this analysis, ANL configured the GREET® model to evaluate the life cycle GHG emissions of current and future technology pathways of petroleum and renewable diesel for ICEVs and HEVs, SMR and renewable hydrogen for FCEVs, and current and low-carbon electricity for BEVs. Additionally, ANL supported ISATT with the team’s roadmap development and target-setting needs.

Objectives

The goal of this task is to identify the C2G GHG emissions associated with current (2021) and future (2030–2035) MHDV technologies, considering a variety of different fuel pathways. The comparison of these vehicles spans multiple powertrains, multiple vehicle classes, and multiple decarbonization approaches for vehicle energy sources. The results are investigated for the assumption that all vehicles have the capacity to carry the same payload, as well as for payload-reduced conditions for BEVs, which may have these limitations in the real world.

Approach

This analysis builds on our previous LCA of GHG emissions and costs of light-duty midsize sedans for a variety of vehicle–fuel pathways [1], [2]. In this effort, we leveraged concepts from those prior studies, including some assumptions and methods; however, we selected MHDVs for both current (2021) and expected future (2030-2035) conditions. This approach to LCA, often referred to as a C2G analysis, considers vehicle and fuel cycles starting from raw material extraction and including fuel production and transport, vehicle manufacturing, vehicle use, and vehicle EOL. The analysis does not include supporting infrastructure systems (e.g., refinery construction and EOL or LCA of roads and bridges). A C2G analysis provides a holistic view of the sustainability performance of vehicle–fuel technologies across multiple metrics. This evaluation is intended to provide a thorough and up-to-date understanding of the sustainability performance of vehicle technologies and fuels to inform policymaking, investments, and analyses.

This C2G analysis focuses on the MHDV market, particularly the Class 6 box truck, Class 8 regional-haul, and Class 8 long-haul segments. The project team evaluates a variety of conventional and alternative vehicle technologies and fuels. In evaluating the vehicle–fuel combinations, we consider a “CURRENT TECHNOLOGY” case (nominally 2021) and a “FUTURE TECHNOLOGY” lower-carbon case (nominally 2035). We use a "pathway" rather than a "scenario" approach. A pathway is defined as a distinct, technically feasible route or sequence of processes starting with one or more feedstocks and ending with an intermediate or final product.

The fuel pathways considered here are shown in Table VI.1.3. All cases assume large-scale production for both fuel and vehicle technologies. The electricity mix used in the FUTURE TECHNOLOGY pathways comes from the 2035 U.S. grid generation mix projected by the U.S. Energy Information Administration in the Annual Energy Outlook 2023 (unless otherwise specified) [3].

Table VI.1.3 Fuel Production Pathways Considered in This C2G Analysis

Fuel	Current Technology Case	Future Technology Case
Diesel	U.S. average crude mix	Renewable diesel (pyrolysis of forest residue)
		Hydro-processed renewable diesel from soybeans
		20% fatty acid methyl ester bio-based diesel (B20) from soybeans[a]
		Gas-to-liquid Fischer–Tropsch diesel (GTL FTD)
		E-fuels (Nuclear electricity + CO_2)
		E-fuels (Renewable electricity + CO_2)
Hydrogen	Centralized NG SMR	Low-temperature electrolysis using wind/solar
		High-temperature electrolysis using nuclear energy
		NG SMR with carbon capture and storage
Electricity	Annual Energy Outlook U.S. average electricity generation mix in 2021	NG advanced combined cycle
		NG advanced combined cycle with carbon capture and storage
		Wind
		Solar photovoltaic
Gasoline (E10) [Class 6 only]	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)
Ethanol (E85) [Class 6 only]	85% corn ethanol (blended with 15% petroleum gasoline blendstock)	85% cellulosic from corn stover (blended with 15% petroleum gasoline blendstock)

[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. FAME is also known as biodiesel. Percentage blending values are by volume.*

In assessing life cycle emissions, this analysis considers emissions associated with the fuel and the vehicle cycle. The C2G GHG emissions assessment was carried out by expanding and modifying the GREET® model suite with input from industrial experts. Figure VI.1.4 shows the main life cycle stages covered by the fuel cycle model (GREET 1) and the vehicle cycle model (GREET 2). The GREET1 model calculates the energy use and emissions associated with the recovery (or growth, in the case of biofuels) of the primary feedstock; transportation of the feedstock; fuel production from the feedstock; and transportation, distribution, and use of the fuel during vehicle operation. The GREET 2 model calculates the energy use and emissions associated with the production and processing of vehicle materials, vehicle manufacturing and assembly, and EOL decommissioning and recycling of vehicle components. GREET 1 contains more than 100 vehicle–fuel system combinations. Fuel types for MHDVs include gasoline, diesel, biofuels, hydrogen, NG-based fuels, and electricity. Figure VI.1.4 provides a GREET 1 fuel production pathway example. Vehicle technologies in GREET 1 for MHDVs include ICEVs, HEVs, BEVs, and FCEVs.

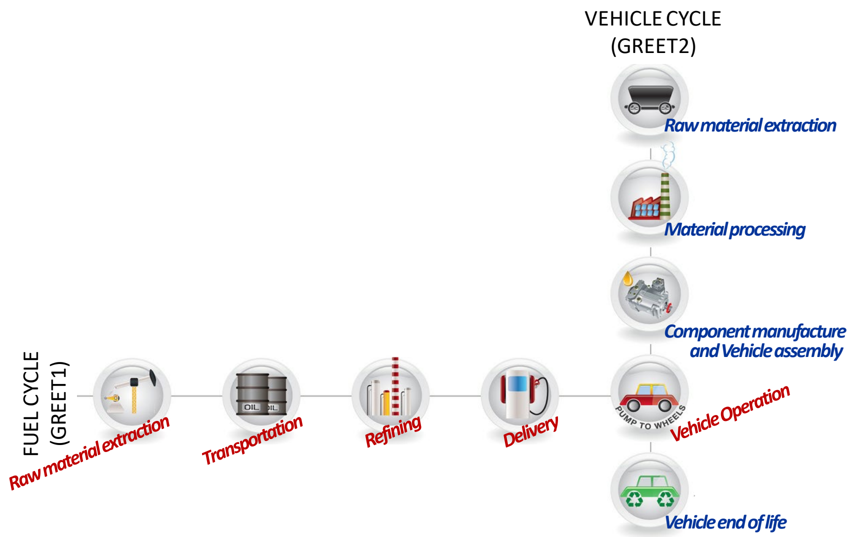


Figure VI.1.4 Combined fuel cycle and vehicle cycle activities included in C2G analysis. Source: ANL

As in our prior analyses, the evaluation of vehicle technologies is conducted using publicly available data and models. Vehicle fuel economies and component sizes are estimated using ANL's Autonomie model, with a consistent set of vehicle performance criteria across fuel–vehicle combinations. Each vehicle is presumed to be optimized for the fuel on which it operates. Inputs to Autonomie are based on vehicle manufacturer information and assumptions made by the authors, along with specific technology assumptions provided by DOE VTO and the Hydrogen Fuel Technologies Office; these inputs are detailed in Islam et al. [4]. Vehicle energy consumption is the most critical attribute in determining fuel cycle performance. In this study, vehicle efficiency is expressed as fuel economy. For the set of vehicles examined, fuel economies are expressed in diesel gallon equivalents (dge) terms.

Additionally, this study considers that future technological progress may vary. Thus, we consider a low technology progression and a high technology progression. These are informed by DOE, automakers, and engineering modeling and are incorporated into the simulations within Autonomie [4].

Results

This study investigates several different vehicle classes and several powertrains while also considering variations in technology advancement (low and high), along with decarbonization of energy sources used within the vehicles; we also consider all results on a per-mile and per-ton-mile condition. Given this large number of options, we constrain our presentation of results here to the high technology progression for the Class 6 box truck and the Class 8 long-haul truck. Doing so allows investigation into important findings of the study while not enumerating all conditions. Also, the high technology progression indicates the greatest opportunities for decarbonization, and representation of these is consistent with our prior studies [1], [2]. Note that Class 6 box trucks are assumed to have a lifetime driving distance of 300,000 miles, while the Class 8 long-haul (and regional-haul) trucks are assumed to have a lifetime of 1 million miles. This lifetime serves as an allocation for the production burden of the vehicle, which allows it to be placed on the same basis as the operational GHG emissions.

Figure VI.1.5 represents a subset of the study results. The figure demonstrates that for the diesel ICEV Class 6 box truck, potential vehicle efficiency gains would bring emissions down from 1,641 g CO_2e/mi (indicated by the black line, which represents CURRENT TECHNOLOGY) to 1,252 g CO_2e/mi (indicated by the red line, which shows 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 to between 180 and 110 g CO_2e/mi, as represented by the endpoints of the grey arrows. We further see that the burden of vehicle production (indicated by the blue line, which represents the case in which the vehicle is operated on a 0 g CO_2e/mi fuel) for the ICEV accounts for 58 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. We similarly see, in Figure VI.1.66, for the diesel ICEV Class 8 long-haul truck, potential vehicle efficiency gains would bring emissions down from 1,830 g CO_2e/mi to 1,126 g CO_2e/mi in a FUTURE TECHNOLOGY case. By using a low-carbon fuel, the emissions could be further reduced to between 174 and 115 g CO_2e/mi, and the vehicle cycle of the future technology condition represents 68 g CO_2e/mi.

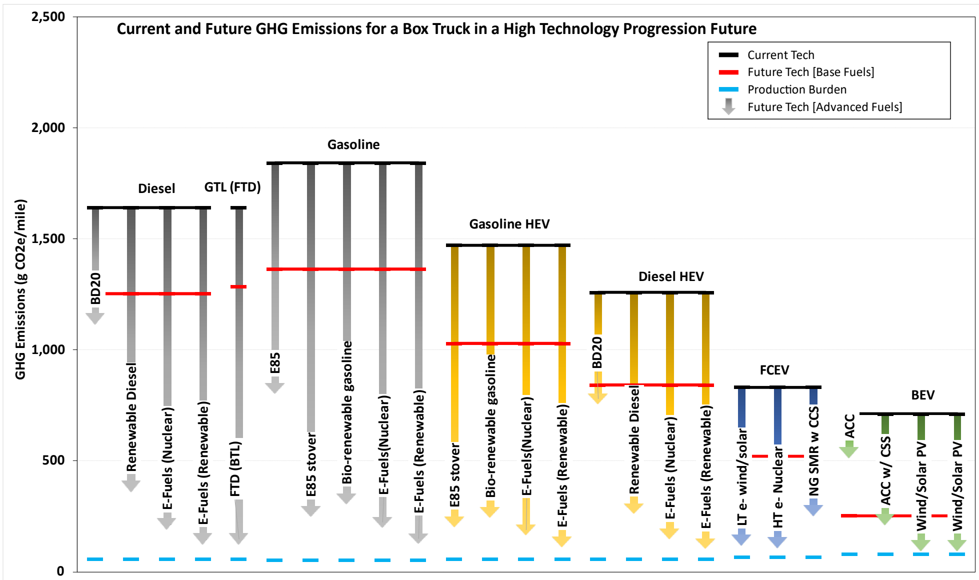


Figure VI.1.5 Per-mile GHG emissions of a Class 6 box truck considering a high future technology progression. Source: ANL

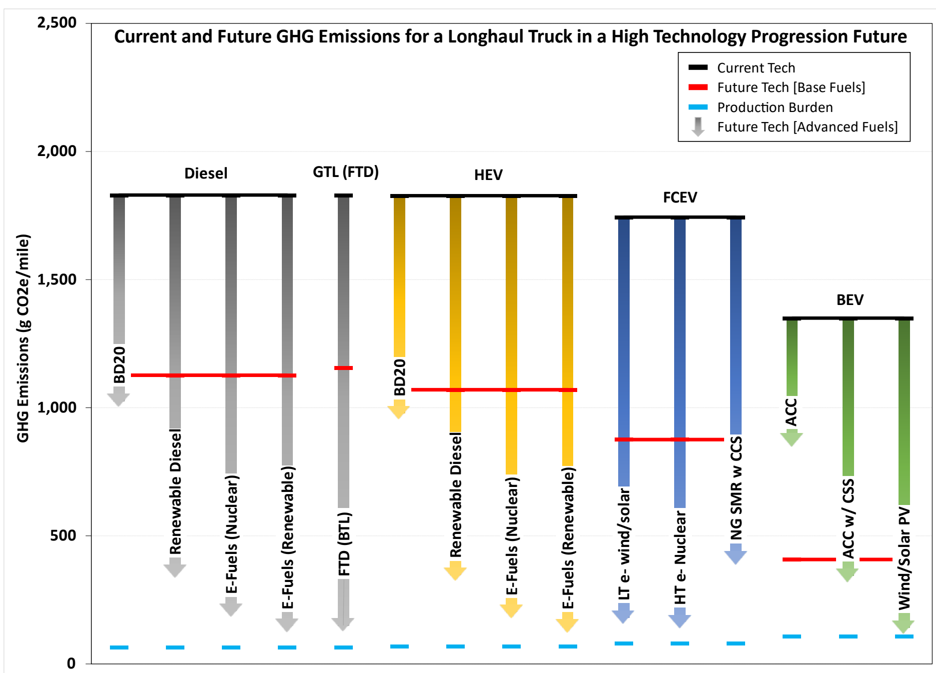


Figure VI.1.6 Per-mile GHG emissions of a Class 8 long haul truck considering a high future technology progression. Source: ANL

Both Figure VI.1.5 and Figure VI.1.6 show that the combination of vehicle efficiency gains and low-carbon fuels GHG emission reductions allows for dramatically increased GHG reductions compared to vehicle gains alone. The down-arrows associated with decarbonized fueling pathways show a plausible reduction of the GHG emissions of the vehicle-fuel pathway from low-carbon fuels and electricity, but the feasibility of achieving the indicated GHG emission reductions were not considered. More broadly, these results demonstrate that large GHG reductions for MHDVs are challenging and require consideration of the entire life cycle, including vehicle manufacture, fuel production, and vehicle operation.

Conclusions

This analysis has found that technology advancement on the vehicle side will be an important facilitator of GHG reduction for MHDVs. Both efficiency improvement and powertrain switching could lead to GHG reductions for these vehicles. However, opportunities for technological improvement appear to be subject to operating conditions, as the GHG reduction for conventional fueling pathways is greater for Class 6 box trucks, which operate on “around town” routes, compared to Class 8 long-haul trucks, which operate across long distances at relatively high, steady speeds. To achieve deep decarbonization, it will be necessary to advance fueling technologies such that the energy sources themselves have much-reduced CO_2e contents.

Key Publications

Select Presentations

1. Kelly, Jarod. 2022. “An All-Hands-On-Deck Approach to Address Lifecycle Emissions.” Invited presentation at KAPSARC’s Future of mobility, October 31.

2. Kelly, Jarod. 2022. “Cradle to Grave Life Cycle Analysis of Light Duty Vehicles Considering Potential Future Vehicle Fuel Pathways.” The Alliance for Vehicle Efficiency, virtual, November 29.

3. Kelly, Jarod. 2022. “Cradle to Grave Life Cycle Analysis of Light Duty Vehicles Considering Potential Future Vehicle Fuel Pathways.” The CRC Sustainable Mobility Workshop at the National Renewable Energy Laboratory, December 13–15.

4. Kelly, Jarod. 2023. “Cradle-to-Grave Life Cycle Analysis of Light Duty Vehicles Considering Potential Future Vehicle-Fuel Pathways in the United States.” Konkuk University, Seoul, Korea, April 6.

5. Kelly, Jarod. 2023. “Cradle-to-Grave Life Cycle Analysis of Light Duty Vehicles Considering Potential Future Vehicle-Fuel Pathways in the United States.” 2023 International Symposium on Automotive Life Cycle Analysis, Seoul, Korea, April 7.

6. Kelly, Jarod. 2023. Invited presentation. 2023 SAE World Congress Experience, Detroit, Michigan, April 18–20.

References

1. Elgowainy, Amgad, Jeongwoo Han, Jacob Ward, Fred Joseck, David Gohlke, Alicia Lindauer, Todd Ramsden, Mary Biddy, Marcus Alexander, Steven Barnhart, Ian Sutherland, Laura Verduzco, and Timothy Wallington. 2016. *Cradle-to-Grave Lifecycle Analysis of U.S. Light Duty Vehicle-Fuel Pathways: A Greenhouse Gas Emissions and Economic Assessment of Current (2015) and Future (2025-2030) Technologies*. ANL/ESD-16/7. DOI:10.2172/1254857.

2. Kelly, Jarod C., Amgad Elgowainy, Raphael Isaac, Jacob Ward, Ehsan Islam, Aymeric Rousseau, Ian Sutherland, Timothy J. Wallington, Marcus Alexander, Matteo Muratori, Matthew Franklin, Jesse Adams, and Neha Rustagi. 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*. ANL-22/27. June 1. https://greet.es.anl.gov/publication-c2g_lca_us_ldv.

3. U.S. Energy Information Administration. 2023. "Annual Energy Outlook 2023." https://www.eia.gov/outlooks/aeo/pdf/AEO2023_Narrative.pdf.

4. Islam, Ehsan Sabri, Ram Vijayagopal, and Aymeric Rousseau. 2022. "A Comprehensive Simulation Study to Evaluate Future Vehicle Energy and Cost Reduction Potential." *Report to DOE, Contract ANL/ESD-22/6.* October.

Acknowledgements

ISATT comprises representatives from DOE, the energy and auto industries, and national laboratory researchers. The team acknowledges the support from experts from these various organizations.

VI.2 Analysis of Employment and Other Economic Impacts of Transportation Electrification (Argonne National Laboratory)

Yan Zhou, Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Lemont, IL, 60565
YZhou@anl.gov

Yue Ke, Principal Investigator
Argonne National Laboratory
9700 S. Cass Ave
Lemont, IL, 60565
YKe@anl.gov

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: October 1, 2022 End Date: September 30, 2025
Project Funding (FY23): $250,000 DOE share: $250,000 Non-DOE share: $0

Project Introduction

Given the urgency of climate change and the need for deep decarbonization, electrification is gaining traction. To succeed at the speed and scale needed, experts agree that a rapid shift from fossil to carbon-free energy must occur across all energy sectors, along with efficiency improvements to mitigate challenges associated with expanding zero and near-zero energy supplies. Clearly, electrification will change how vehicles are manufactured and used, the infrastructure to maintain and support them, and the jobs associated with moving people and goods. But beyond direct changes, several "upstream" and "downstream" effects are likely. The former will include shifts in supply chain processes and industries; the latter will include shifts in interconnected industries gaining (or losing) jobs from induced effects. Since changes will extend beyond the production and use of vehicles and fuels, an integrated approach to economic analysis—comparable to estimating Scope 1, 2, and 3 emissions in lifecycle analysis—is needed to fully account for upstream and downstream effects. This project will assess the jobs and other macroeconomic impacts of various transportation decarbonization pathways, with a focus on electric vehicles (EVs) and charging infrastructure. The project team will use Argonne's JOBS EVSE [1], which estimates macroeconomic impacts from deploying and operating charging infrastructure, and JOBS EV, which estimates impacts from all phases of EV production. This project is a three-year U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) lab annual operating plan (AOP) project that started in Fiscal Year (FY) 2023.

Objectives

The main objective of this project is to quantify the potential macroeconomic impacts of deep decarbonization via electrification of the transportation sector. The project includes the following tasks:

1. **Conduct a literature review and industry stakeholder interviews:** Review the literature on EV impacts throughout the vehicles' life cycles to identify key factors affecting job creation and engage with industry stakeholders to better understand manufacturing industries' viewpoints and decision-making processes

2. **Develop a database to assess jobs, wages, and gross domestic product (GDP) impacts:** Develop a database of industries, business listings, employment job types, and quality of jobs corresponding to

key stages of the life cycles for light-, medium-, and heavy-duty EVs and electric vehicle supply equipment (EVSE) production and use

3. **Develop electrification scenarios and analyze macroeconomic impacts by life cycle stage:** Define electrification scenarios based on stakeholder inputs, DOE and VTO targets, prior VTO-supported analyses, and the database developed in Task 2

4. **Quantify shifts in macroeconomic indicators (jobs, wages, GDP) by location:** Quantify changes in number of jobs and types of jobs by industry and location for each scenario developed in Task 3

5. **Identify job creation opportunities and potential energy equity and environmental justice outcomes:** Identify job creation opportunities for new skilled job types in near-, medium-, and long-term scenarios, and identify alternative industries in which traditional automotive job skillsets may also be applied

This project provides data and information on the current state of U.S. auto-manufacturing-related industries and forecasts the expected macroeconomic impacts of transitioning to large-scale EV market penetration. Deliverables include reports and presentations to DOE VTO.

Approach

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

Conduct a literature review and industry stakeholder interviews: This task reviews current and past literature—including academic journals, industry whitepapers, and other reports—to identify factors affecting job creation. Additionally, the research team will engage with industry stakeholders through one-on-one interviews and the formation of an advisory group to validate findings and ensure the outcomes of each task are inclusive and meaningful.

Develop a database to assess jobs, wages, and GDP impacts: This task lays the foundational groundwork for the remaining tasks by developing a database of industries, businesses, employment, job types, and job quality corresponding to key stages of the life cycles for light-, medium-, and heavy-duty EVs and EVSE production and use. Stages in the vehicle cycle extend from raw materials extraction and processing to product delivery and use; stages in the energy cycle extend from power generation to EV charging. Disaggregating economic features by life cycle stage is particularly relevant to addressing impacts associated with network upgrades to accommodate EVSE and anticipated load growth. This database helps set the parameters needed to design scenarios such as 50% battery electric vehicle (BEV) sales targets, 500,000 EVSE deployments, and net-zero-carbon pathways.

Develop electrification scenarios and analyze macroeconomic impacts by life cycle stage: Electrification scenarios are defined based on stakeholder input, DOE and VTO targets, and prior VTO-supported analyses. Scenarios incorporate a range of assumptions, including Administration goals and industry sustainability objectives, as well as potential barriers and stakeholder concerns. From the overall electrification scenarios, a series of life-cycle-based scenarios is derived to estimate macroeconomic impacts at key life cycle stages as defined by the Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET®) model, including raw material extraction, intermediate component manufacturing, final component manufacturing and assembly, shipping and sales, equipment operation, and end-of-life disposal/recycling.

Quantify shifts in macroeconomic indicators (jobs, wages, GDP) by location: By applying the database created in Task 2, this task analyzes how widespread electrification in the automotive sector changes jobs, both by type and by location. The aim is to identify the potential industries that will face large-scale job restructuring and build on the findings of previous high-level analyses. The analyses can be further disaggregated into state, county, and plant levels to allow for higher-resolution estimations of gross macroeconomic impacts.

Identify job creation opportunities and potential energy equity and environmental justice outcomes: The job creation opportunities of widespread electrification can be identified at community levels. Additionally, the project team will identify potential environmental justice and equity effects of transportation electrification via a focus on distribution of impacts on different communities. To this end, the team will use case studies centered around areas of interest. A geospatial economic and environmental impacts inventory will also be developed for national, regional, and local levels.

Results

The literature review focused on two main subjects: the BEV supply chain and anticipated economic impacts. Outsourcing from original equipment manufacturers (OEMs) to large suppliers may increase in the near term to leverage economies of scale. Combined with mergers and acquisitions, this may result in larger Tier 1 suppliers. However, OEMs may be reluctant to wholly outsource because of highly proprietary, sensitive, and safety-critical vehicle systems. Long-standing relationships and track records for component design, engineering, and manufacturing at scale give global diversified Tier 1 suppliers advantages over new/niche suppliers. Traditional internal combustion engine (ICE) component suppliers remain diligent in diversifying product portfolios to avoid disintermediation over the long run with the evolution of technologies. Battery cell and pack suppliers are an exception because they typically supply only that specific system and because the technology is at a relatively early stage.

Of the anticipated economic impact analyses available, the majority were state-specific reports that relied on input–output modeling (e.g., IMPLAN, Regional Input-Output Modeling System (RIMS II), etc.) and shift share analyses. Typically, only direct effects on jobs were reported. While some analyses report indirect effects, none report induced effects, indicating that no holistic studies are available. Further, no agreement could be found in the literature regarding a unifying set of preliminary assumptions, methods, or temporal scope. For instance, analyses conducted on the impact of transportation electrification in Illinois found job creation ranging from 2,850 to 79,500 new jobs, depending on the method, assumptions, and time horizon.

Interviews with OEM and Tier 1 suppliers revealed five key takeaways. ICE vehicles and EVs will share production lines at assembly plants until EV sales volumes reach a breakpoint, typically 20,000–30,000 vehicles. Although this practice is inefficient from a labor perspective, sharing production lines is efficient from a capital perspective. While each OEM will continue to make vertical integration decisions based on internal make–buy studies, OEMs nonetheless show an industry trend toward vertical integration that includes power electronics, control drive units, charging and cooling systems, and motor manufacturing. An OEM move toward increasing automation depends on the expected vehicle production volumes. However, for suppliers, the automation decision depends on the complexity of assembly—for instance, subcomponents that are floppy do not lend themselves to automation. Discussions over the effects of the Inflation Reduction Act (IRA) during the interviews centered around the uncertainty over how long the IRA will last, which made it difficult for suppliers to plan long-term strategies; for suppliers, the United States–Mexico–Canada Agreement may have a larger effect on on-shoring decisions than the IRA. Foreign OEMs with U.S. assembly plants are more affected by the IRA than domestic OEMs, as the Act upends traditional manufacturing approaches for new vehicles (i.e., reach a threshold of vehicles sold before onshoring). Interviewees indicated that OEMs are making upstream deals or engaging in joint ventures to offset supply chain uncertainties. Similarly, the Tier 1 suppliers we spoke with were worried about Tier 2 and 3 suppliers staying solvent. OEMs also noted that they are facing labor shortages, especially in software engineering.

The second project task is to develop a database of companies involved with motor vehicle manufacturing at all stages of the motor vehicle life cycle, including raw material extraction, subcomponent and component manufacturing, and vehicle assembly. Using Dun and Bradstreet Hoovers™ business listings data, we document the global vehicle manufacturing supply chain with a focus on North American-based, and particularly U.S.-based, facilities. We do this for all subcomponents and components made of aluminum, steel, and plastic, as well as for battery cells and packs materials. Figure VI.2.1 shows the main components of the top 20 companies by annual sales for aluminum subcomponent manufacturing. The businesses' products included in the figure are in Tiers 2 and 3. A separate analysis is being conducted for Tier 1 manufacturing and OEM assembly.

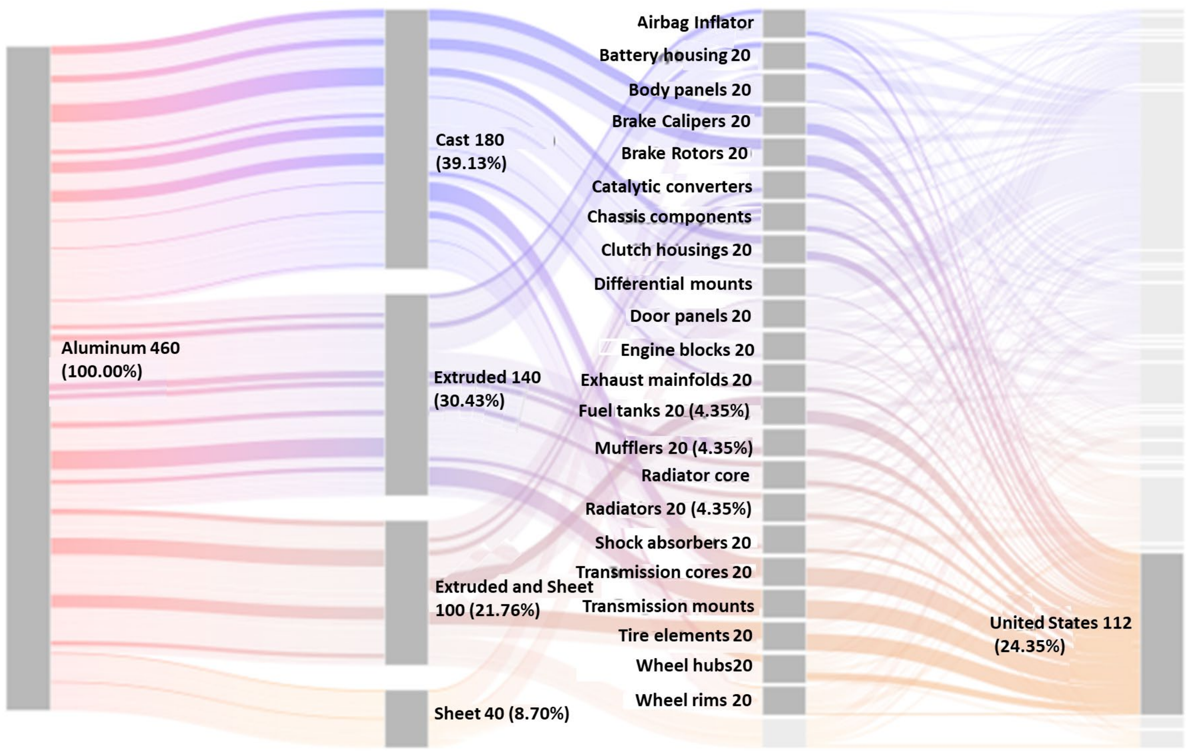


Figure VI.2.1 Aluminum subcomponent manufacturing by country. The types of aluminum shown in the second column are consistent with GREET aluminum types. The third column shows the subcomponents produced using the types of aluminum. The thickness of the lines between the third and fourth columns indicates the proportion of top 20 U.S. companies engaged in manufacturing each subcomponent. Source: Argonne National Laboratory

From these data, we can see that the supply chain is global at Tiers 2 and 3, despite the United States–Mexico–Canada Agreement and IRA, for non-powertrain-specific components—in stark contrast with Tier 1 and OEM assembly pipelines. Many small companies make up Tier 2 and are in the United States. Tier 2 and 3 companies are more vulnerable to shocks than larger Tier 1 firms, as Tier 2 and 3 companies have lower operating margins and typically specialize in a smaller portfolio of products. These observations have been corroborated by interviews with the Tier 1 stakeholders.

Preliminary investigation of workforce development and EV manufacturing jobs shows that most skillsets used in ICE vehicle assembly will also be relevant for EV assembly. The key difference is that EV assembly will require workers with training in high-voltage applications. The following table shows the occupations that will be needed for EV manufacturing, the minimum level of education for those occupations, and median annual wages (in 2010 dollars).

Table VI.2.1 EV Manufacturing Occupations, Minimum Education Required, and Median Annual Wages

Occupation Description	Minimum Education	Median Annual Wages (2010)	Occupation Description	Minimum Education	Median Annual Wages (2010)
Chemist	Bachelor's	$68,320	Software developer, applications	Bachelor's	$94,680
Materials scientist	Bachelor's	$84,720	Commercial and industrial designer	Bachelor's	$67,790
Chemical engineer	Bachelor's	$97,480	Electrical and electronic equipment assembler	On-the-job training	$29,470

Occupation Description	Minimum Education	Median Annual Wages (2010)	Occupation Description	Minimum Education	Median Annual Wages (2010)
Electrical engineer	Bachelor's	$87,580	Electromechanical equipment assembler	On-the-job training	$32,430
Electronics engineer, except computer	Bachelor's	$100,450	Engine and other machine assembler	On-the-job training	$47,440
Industrial engineer	Bachelor's	$77,160	Team assembler	On-the-job training	$32,500
Materials engineer	Bachelor's	$89,000	Computer-controlled machine tool operator, metal, and plastic	On-the-job training	$35,580
Mechanical engineer	Bachelor's	$81,290	Machinist	Apprenticeship	$40,810
Mechanical engineering technician	Associate's	$52,950	Industrial production manager	Bachelor's	$91,460
Mechanical drafter	Associate's	$53,840	Automotive service technician	Vocational or certification	$33,010

Conclusions

The transition to electrified transportation will have far-reaching effects across many industries and sectors, particularly once one considers the full motor vehicle manufacturing supply chain and the diverse services within an ecosystem required to support BEVs throughout the vehicle life cycle. FY 2023 efforts have focused on fleshing out the scope of this analysis by conducting a literature review, interviewing industry stakeholders, and developing a database of suppliers to assess economic impacts. The literature review revealed that many states with considerable vehicle manufacturing footprints are aware of the potential economic impacts EV manufacturing will have. However, these studies tend to be limited to a single state and to examining electrification's effects only on OEMs and Tier 1 suppliers. Furthermore, these studies use differing assumptions and a variety of methods in estimating impacts. Conversations with stakeholders indicate that industry players have differing concerns depending on where they are positioned in the supply chain. For instance, OEMs are worried about being able to hire enough programmers, as EVs will have more software than ICE vehicles, while Tier 1 suppliers are concerned with being able to adequately source components from Tier 2 and 3 suppliers. The database developed in FY 2023 consists of OEMs and companies involved in Tiers 1 and 2 in the automotive supply chain; upcoming efforts will enhance this database to cover the occupations and skillsets involved in these manufacturing sectors, enabling analysis of changes in job types and counts by location due to the transition to EVs.

Key Publications

Ke, Yue, and Matthew R. Sloggy. 2023. "Quantifying the Economic Impacts of Electric Car Production." Agricultural and Applied Economics Association 2023 Annual Meeting, July 23–25, Washington, DC. Presentation 26386, record identifier 335677.

References

1. Argonne National Laboratory. n.d. "Jobs EVSE." https://www.anl.gov/esia/jobs-evse.

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

Dave Mullaney, Principal Investigator
Rocky Mountain Institute
22830 Two Rivers Road
Basalt, CO 81621
E-mail: DMullaney@rmi.org

Lynn Daniels, Project Manager
Rocky Mountain Institute
2490 Junction Place, Suite 200
Boulder, CO 80301
E-mail: LDaniels@rmi.org

Raphael Isaac, DOE Technology Development Manager
U.S. Department of Energy
E-mail: Raphael.Isaac@ee.doe.gov

Start Date: October 1, 2021	End Date: December 31, 2023	
Project Funding (FY23): $215,275	DOE share: $196,392	Non-DOE share: $18,884
Total Project Funding: $377,666	Total DOE share: $339,899	Total non-DOE share: $37,767

Project Introduction

Over 400 million metric tons of carbon dioxide equivalent (CO_2e) are emitted annually by over-the-road freight movement in the United States [1]. These vehicles drive a collective 300 billion miles [2] and move 10 billion tons of freight annually [3]. The environmental burden of moving goods—for vehicles from delivery vans to long-haul trucks—contributes to local air pollution and global greenhouse gas emissions. Medium- and heavy-duty (MDHD) vehicle classes contribute 23% of the U.S. transportation sector's carbon footprint [3]. With this sizable contribution to emissions, electrifying MDHD vehicles will be critical to meeting climate goals.

Today, there are more than 150 electric MDHD (eMDHD) vehicle models available in the United States [4], with more scheduled for release in the coming years [5], [6]. However, 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 required. The goal of this project is to identify the most likely "electrifiable" trucks in 15 states that have enacted freight electrification regulations and to quantify the energy and charging 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

In Budget Period 1, we defined 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 aims to capture the segment of the trucking market most easily electrified in the next one to three years.

During Budget Period 2, we completed our analysis of trucking telematics data in the 15 states that are working toward implementing the Advanced Clean Trucks (ACT) rule [7]. From this understanding of how trucks currently operate, the project team computed the energy needed to electrify these duty cycles, the necessary charging infrastructure under various scenarios, and load curves. We have built a public-facing data explorer with maps and plots that is currently in public beta testing, with its final version expected to be published in January 2024 at https://rmi.org/early-trucking-electrification-in-act-states. Lastly, we have drafted a final report synthesizing our results and key insights, also to be published in January 2024.

The project obtained truck telematics data from Geotab [8]. From observed driving patterns of these vehicles, we can determine which trucks could be replaced by electric vehicles based on existing electric vehicle technology and charging infrastructure. We estimated required daily energy demand per truck by assuming that medium-duty (MD) trucks consume, on average, 1.3 kWh/mile and heavy-duty (HD) trucks consume 2.5 kWh/mile. We then 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. The magnitude of the load was adjusted to ensure that the total area under the curve is equal to the total daily energy required by the trucks.

Results

The project team analyzed telematics data for 592,000 electrifiable MD trucks and 388,000 electrifiable HD trucks. The analysis was used to answer the questions below.

1) How much energy and how many chargers will eMDHD vehicles need?

Figure VI.3.1 shows the 75th percentile of daily mileage driven and the corresponding energy needs in kWh for MD and HD trucks for each of the 15 states (state-level values are an unweighted average of all county values within the state). Nationwide, the average 75th percentile of daily distance traveled for electrifiable trucks is 121 miles for MD trucks and 156 miles for HD trucks, corresponding to average daily energy demands of 172 kWh for MD trucks and 427 kWh for HD trucks. Based on this, compliance with the ACT rule is achievable until 2040 with today’s technology, and states should have few reservations about committing to ACT sales targets.

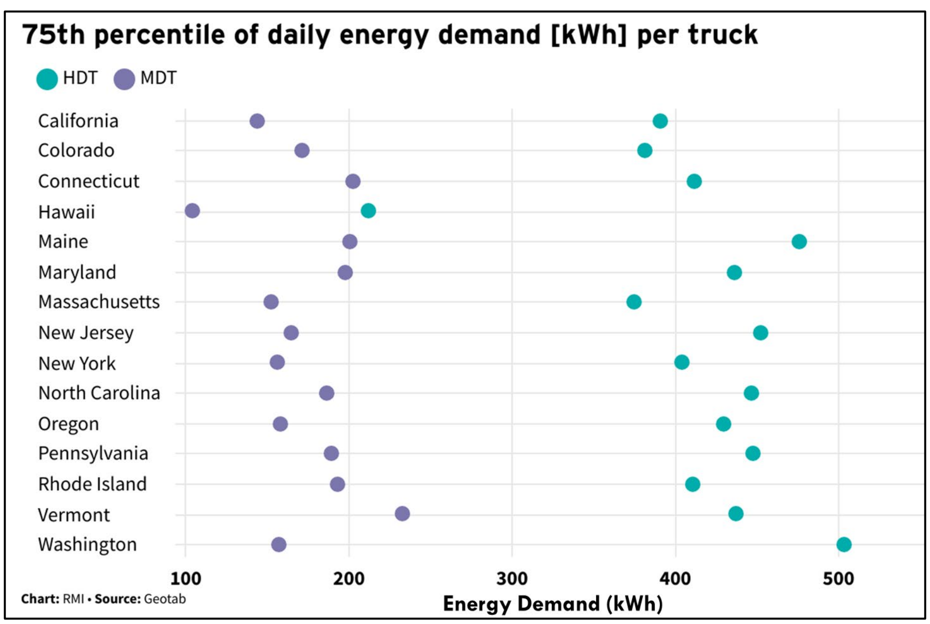
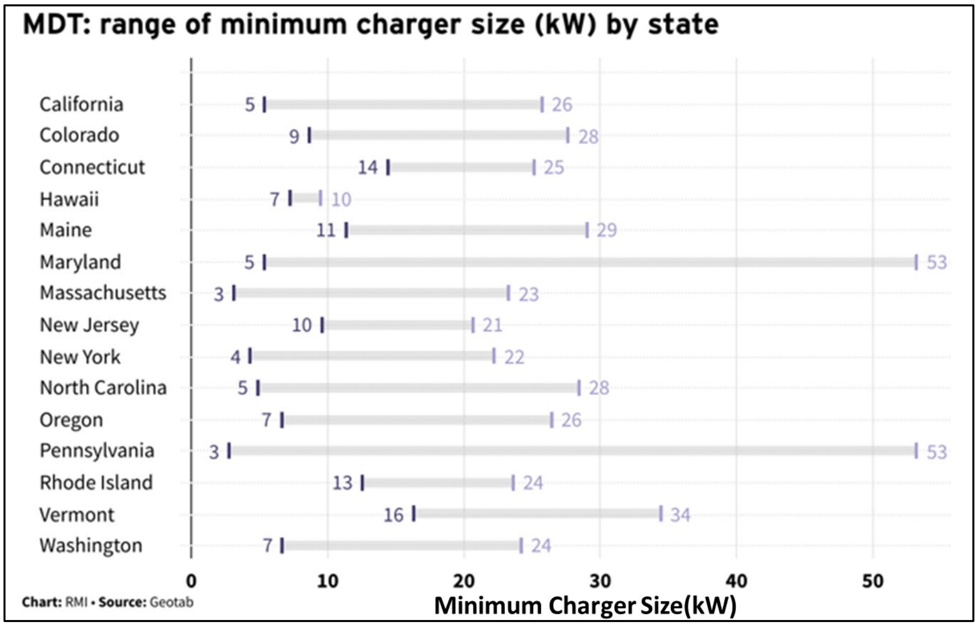
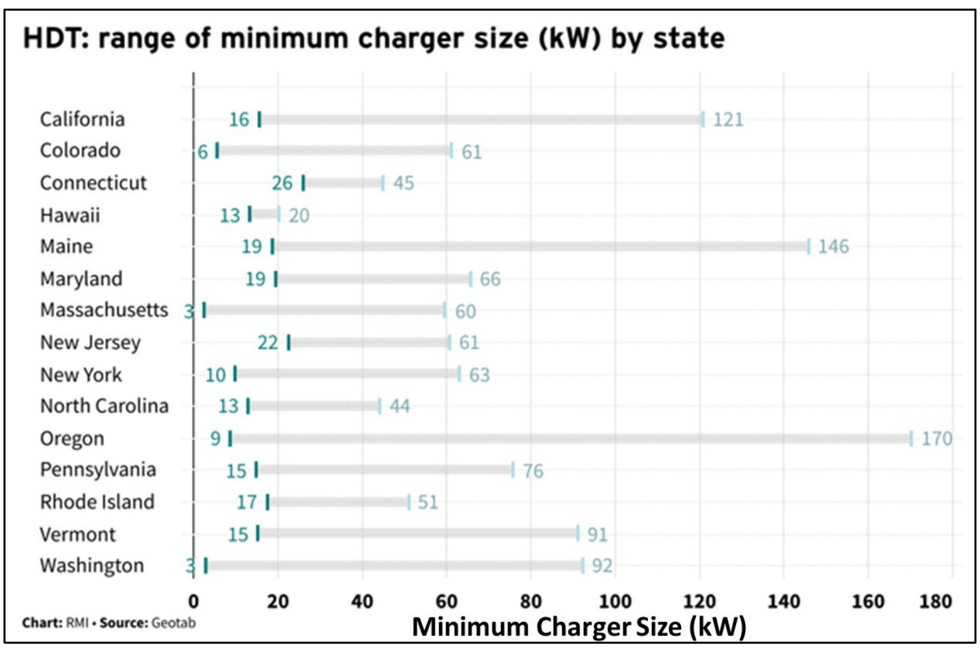


Figure VI.3.1 Statewide daily energy (kWh) needed per truck for MD and HD trucks. Source: RMI, [7] The project team then estimates the minimum charger size (kW) needed for a truck to fully charge, shown in Figure VI.3.2. (The range in the figure shows variation in results for the counties within each state.) Findings indicate that a 50 kW charger will be sufficient for almost all truck needs; a relatively higher-powered 150 kW charger would fully charge most vehicles in under three hours; and a 75 kW charger would do the job for eMD vehicles in three hours and eHD vehicles in seven hours (effectively overnight at a depot).



(a)



(b)

Figure VI.3.2 Range of minimum necessary charger size (kW) for (a) eMD land (b) eHD trucks to fully recharge at depot, by state. Source: RMI, [7]

2) Where will energy and power demand increase, and how will this increase impact the electric grid?

As shown in Figure VI.3.3, energy demand from electrifiable trucks is highest in urban areas because these densely populated areas tend to have more trucks. Rural areas have the lowest energy demand, which aligns with general industry sentiment that rural counties should be concerned mostly with corridor charging for long-haul trucks. However, in many cases, estimated load from electrified trucks that depot in rural counties—primarily MD delivery vehicles—can exceed 1 MWh, roughly equivalent to a neighborhood of 30 homes. Suburban and exurban counties fall in between, with an intermediate but still sizable energy demand.

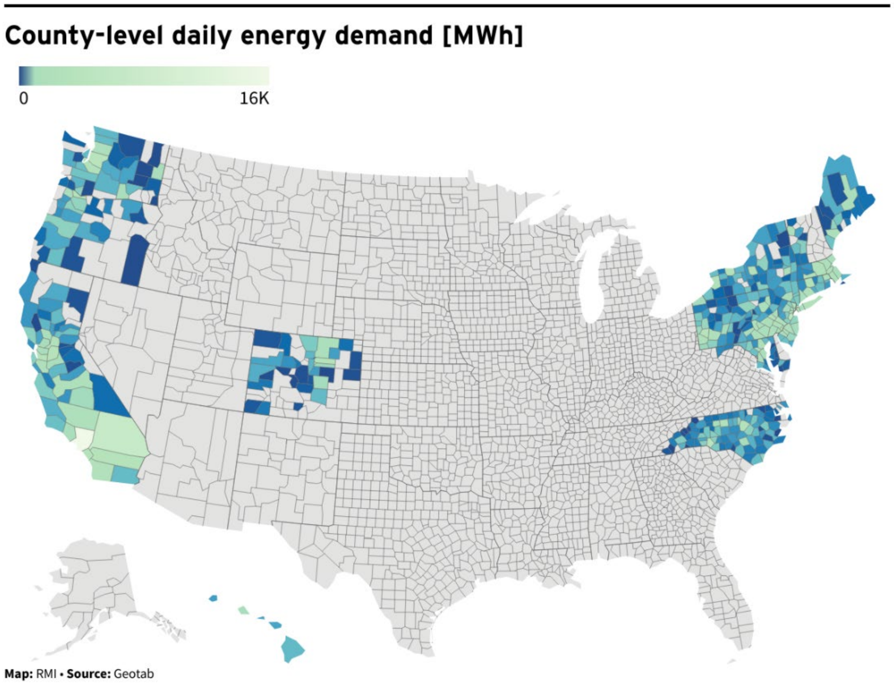
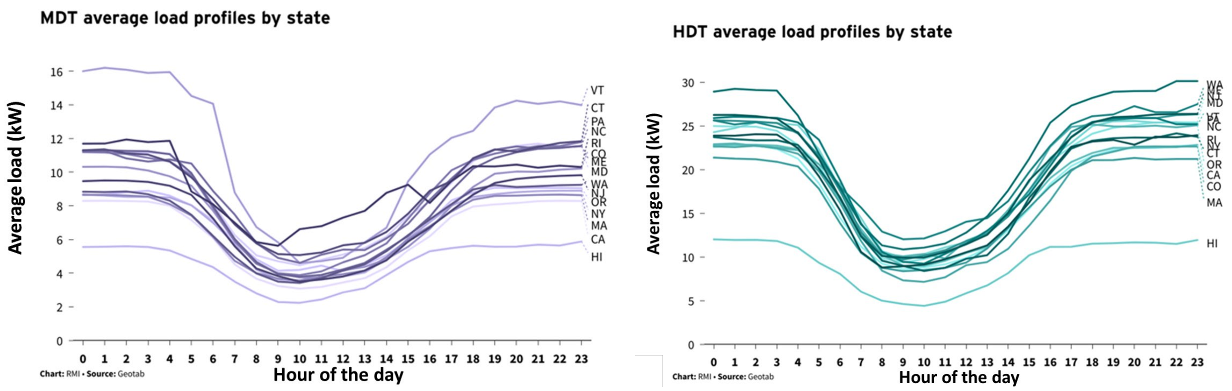


Figure VI.3.3 Map of county-level daily energy demand from MD and HD trucks. Source: RMI, [7]

How this impacts the local grid will depend on how fleets respond to the transition to electric trucks. What we can reasonably expect is that fleets will seek the most cost-effective path forward. It is quite possible that suburbs and exurbs with newer grids, more available grid capacity, and cheaper real estate than in urban areas will prove attractive to site new depots in the coming decade. Today, we are already seeing fleets choose to site depots in less dense areas, often located near lower-income communities that will be disproportionately impacted by emissions from trucks loading or unloading at these locations—all the more reason to ensure those trucks are electric. Over the next decade, policymakers and utilities need to pay close attention to industry trends and how fleets balance costs and make depot-siting decisions.

3) Where is infrastructure investment needed, and how can costs be reduced?

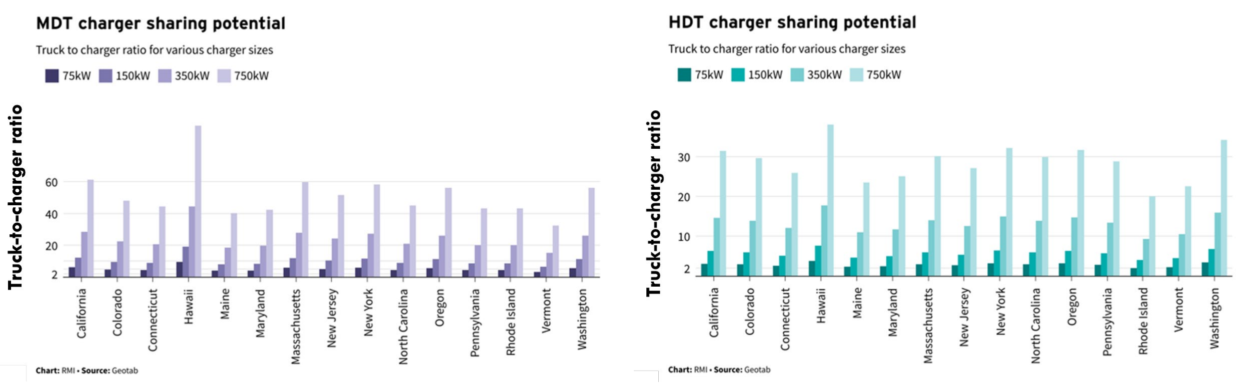
The project team models 24-hour load profiles for each county, shown in Figure VI.3.4, using a Monte Carlo simulation to statistically estimate the percentage of trucks parked at depots during each hour of the day. For our baseline charging scenario, we assume any truck parked at depot is charging, and we sum up the total trucks charging during each hour. We then adjust the magnitude of the load curve to ensure that the area under the curve is equal to the total daily energy needed by all electric trucks to fully recharge. This methodology is useful because it does not require that we assume a particular charger power or portfolio of chargers to meet the energy demand each hour. The resulting load profiles show, as expected, that electric load at the depot peaks in the evening and overnight hours, when trucks are parked, and is significantly lower during the day, when trucks are in operation.



(a) (b)

Figure VI.3.4 Load profiles for (a) MD and (b) HD trucks averaged over all counties, by state. Source: RMI, [7]

To mitigate grid impacts, the project team then looked at the potential for trucks to share a single charger to reduce instantaneous peak load (both at individual sites and for the grid), shown in Figure VI.3.5, in terms of a truck-to-charger ratio for different charger sizes, up to 750 kW. Remarkably, for the readily available 150 kW charger, approximately 10 typical MD trucks or 5 HD trucks could share a single charger.



(a) (b)

Figure VI.3.5 Potential to share chargers shown as truck-to-charger ratio (y-axis) for varied charger power for (a) MD and (b) HD trucks by state. Source: RMI, [7]

As noted in the discussion of Figure VI.3.2, electrifiable trucks can also have relatively short charging times. This means not only that fleets can readily share chargers across multiple trucks operating under similar duty cycles, even with lower-powered 75 kW chargers, but also that fleets have flexibility to choose when they charge their trucks in order to minimize grid impacts and the subsequent need for grid infrastructure upgrades. In other words, if a truck arrives at depot at 6 PM, rather than charging immediately, the operator can wait to charge until later—possibly taking advantage of favorable electricity prices and avoiding peak load on the grid—while still knowing the truck will be fully charged by the morning.

4) How should stakeholders prioritize investments to ensure they are made equitably?

Our analysis highlights the need to direct significant investments toward fleets, as well as to the development of a robust public charging network. However, deciding where to prioritize these investments is not simply a matter of knowing where estimated energy demand will be highest (this would provide suburbs, exurbs, and rural areas with very little investment). Policymakers must balance many factors when prioritizing investments: fleet needs (e.g., counties with high truck populations or through which freight corridors pass), equity (e.g., investing in underserved or low-income communities), health (e.g., communities with poor air quality or increased incidence of respiratory illness), and grid impact. For this reason, the project has published an accompanying data explorer where all data found in this report is available for readers to explore alongside many different map layers, available at https://rmi.org/early-trucking-electrification-in-act-states/.

Recommendations for Stakeholders

Lastly, our work highlights key actions that utilities and their regulators, policymakers, fleets, EV service providers, and site operators can each take to ensure a carbon-free trucking future. Key recommendations are below.

For utilities and regulators:

- Combine travel data with distribution grid hosting capacity to proactively plan and build grid infrastructure where eMDHD truck demand is expected.
- Hire staff dedicated to electric transportation to reduce wait time for conducting site-specific grid impact studies and processing interconnection requests and to engage with fleet customers.

For policymakers that have adopted, or are considering adopting, ACT regulations:

- Support fleets with investments to reduce transition costs, including subsidies for site assessments or grid impact studies, chargers, and charger installation.
- Invest in corridor charging to support higher-mileage trucks.
- Watch industry trends for how fleets choose to site new depots. Weigh investments in underserved areas to attract fleets to depot in those areas.

For fleet owners and operators:

- Analyze your fleet's data to assess electrification potential based on actual duty cycles and operational needs. Develop an electrification plan and share your plan with your utility early.

Conclusions

Electric trucks are here today. Model availability, increased battery capacity and range, fleet commitments, and regulations such as ACT are accelerating their adoption. Lack of adequate charging and grid infrastructure will be the primary bottleneck that could impede the transition to electric trucks and slow progress toward eliminating tailpipe emissions. There is urgency in taking meaningful steps to build electric truck charging infrastructure and support fleet owners as they navigate compliance with the ACT rule and the transition to electric trucks.

A public beta version of the user-facing tool is currently available online at https://rmi.org/early-trucking-electrification-in-act-states. We expect to release a final version of the tool and publish our final report, both in January 2024.

References

1. US Environmental Protection Agency, https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions accessed March 10, 2023.
2. U.S. Energy Information Administration, https://www.eia.gov/outlooks/aeo/
3. Statista, https://www.statista.com/statistics/1140181/volume-freight-trucks-united-states/ accessed March 10, 2023.
4. Ibid

5. "Trends in Electric Heavy Duty Vehicles", https://www.iea.org/reports/global-ev-outlook-2022/trends-in-electric-heavy-duty-vehicles accessed March 10, 2023.

6. North American Council for Freight Efficiency, https://nacfe.org/research/electric-trucks/ accessed March 10, 2023.

7. "Clean Trucks from Coast to Coast", Atlas EV Hub, https://www.atlasevhub.com/clean-trucks-from-coast-to-coast/ accessed March 10, 2023.

8. Geotab, https://www.geotab.com/

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